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Military Operations Research

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Letter From The Editor
Dr. Greg Parnell, FS

QUADRENNIAL JOURNAL REVIEW

Our objective is to make *Military Operations Research* the journal of choice for military operations research professionals. We are rapidly approaching the end of our fourth year of *Military Operations Research.* Since many of you are preparing for the Quadrennial Defense Review, I thought it would be appropriate to have our own quadrennial survey to seek feedback from the membership on the past journal issues and solicit your ideas for future issues. Please answer the following questions:

	Strongly Disagree	Disagree	Indifferent	Agree	Strongly Agree
The articles provide sufficient information to be understood.					
I have used one or more journal articles in my professional work.					
I would like to see tutorial articles that describe new military OR techniques					
Theoretical articles are the most useful journal articles.					
Applications articles are the most useful journal articles.					
I would like to see more theoretical articles.					
I would like to see more applications articles.					
I would like to see more heritage articles.					
I would like to see articles by senior military analysts on their lessons learned in military OR.					

Please provide any explanations of your answers or additional comments/suggestions.

You can fax, mail, or email your answers to me at:

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MANOEUVRE WARFARE: SOME CONDITIONS ASSOCIATED WITH SUCCESS AT THE OPERATIONAL LEVEL

by D. Rowland, L. R. Speight and M. C. Keys

This paper is concerned with the conditions likely to enhance the chances of achieving a breakthrough in modern manoeuvre warfare, and then of achieving success in the subsequent campaign. The study which it describes was based on some 159 battles, which a military historian assessed in terms of the success criteria just mentioned, and also rated in terms of some 32 qualitative factors. Of these factors it seems that the achievement of surprise; the employment of aggressive ground reconnaissance; and the condition of air superiority enjoyed by the attacking side, were most strongly associated with success. The study also emphasized the positive relationships which existed between a high rate of terrain capture, a favourable loss ratio and the probability of a favourable campaign outcome. The paper concludes with some discussion of these results, and draws out some implications for the future of battle modelling at the operational level.

EXPLORING A RELATIONSHIP BETWEEN TACTICAL INTELLIGENCE AND BATTLE RESULTS

by MAJ E. Todd Sherrill and
Dr. Donald R. Barr

Provided that current doctrine and organization remain the same for a Battalion Task Force, to what degree does increased intelligence information translate into successful land combat operations? Results that we report here suggest a surprisingly modest gain. Of particular interest is the relative small increase in measurable results observed between operations conducted with intelligence products that units can currently expect to have and those operations conducted with "perfect" intelligence information. Additionally, this paper proposes a new MOE for measuring how much information one has about his opponent. The experiment and the methodology have received much acclaim from the Joint Staff, J6 that doctrine and organization must co-evolve with technology in order to receive order of magnitude gains in effectiveness and that additional research using our methodology would be very helpful.

ILLNESS INCIDENCE DURING MILITARY OPERATIONS AS A SOFT OPERATIONS RESEARCH FACTOR

by Christopher G. Blood

Medical and manpower planners must factor in the impact of unit attrition on the resource requirements of combat operations. While wounded-in-action (WIA) and killed-in-action (KIA) incidence are the most conspicuous examples of battlefield attrition, the incidence of disease and nonbattle injuries (DNBI) also represents a substantial source of personnel noneffectiveness. For operations of moderate to high battle intensity, a significant statistical relationship was observed between casualty rates and DNBI incidence. The dynamics of battlefield DNBI attrition was postulated as the confluence of naturally occurring (peacetime) DNBI incidence with increases in illness incidence resulting from battle fatigue and a weakened immunological system's ability to fend off disease.

REALTIME LEARNING OF DOCTRINE AND TACTICS USING NEURAL NETWORKS AND COMBAT SIMULATIONS

by Dr. John D. Morrison

Limitations of the traditional Artificial Intelligence paradigm restrict its capacity to support manageable and verifiable knowledge base development for expert system simulations. This report argues that because expertise acquired in dynamic military domains is associated with unique aspects of memory and action-response sequences that are resistant to word-based cues and expression, an alternative model is required for acquiring and representing knowledge in these competitive environments.

Motivated by an emerging research into adaptive and neural models, this report documents a USA TRADOC supported research program that proposed

and evaluated an adaptive model within the Army's high-resolution combat simulation—CASTFOREM. The prototype was designed to support a synthetic model of intelligence that represents complex goal functions, rule-based (deductive) reasoning in the presence of environmental activity that is consistent with expectation, as well as goal-based (inductive) reasoning in the presence of uncertainty—unfamiliar patterns of activity.

The experiment demonstrated that the prototype is not only capable of generating effective tactics, but the prototype converges to stable, rule-based behavior quickly and efficiently. These results motivate further research into the application of intelligent simulations to broader, long-term goals such as developing and optimizing tactics for developmental hardware and software systems.

LOCATIONAL ANALYSES OF MILITARY INTELLIGENCE GROUND FACILITIES

by A. Mehrez, M. Eben-Chaime and J. Brimberg

This paper has many contributions. First, an optimization model is developed for the design of ground intelligence systems, a routine task in military intelligence. The model turned out to be new in the location literature, differing from the classical p-median, maximal cover, set covering problems, etc. Second, the integrality of most model variables, an attribute that is most significant in terms of computational tractability, is shown analytically. The design of ground intelligence system is not a trivial task and design quality might be critical to the success of the intelligence operation. The model presented in the paper constitutes an effective and efficient tool that can significantly enhance design quality. Third, insight are gained through computational experiments, including some non-intuitive results such as the large target coverage that can be obtained by very few facilities. Finally, applicative extensions are discussed in details.

SCHEDULING OF MILITARY VEHICLES THROUGH THE DELIBERATE NUCLEAR, BIOLOGICAL, AND CHEMICAL DECONTAMINATION PROCESS

by Georgia-Ann Klutke and Valentin Novikov

The risk to military personnel by the threatened use of chemical weapons during Desert Storm operations in 1992 has led to a reexamination of existing directives for decontaminating exposed troops and equipment. In studying the logistical aspects of the decontamination process, the authors developed a stochastic scheduling model of nuclear, biological, and chemical decontamination activities. An analysis of the model suggests improved strategies for sequencing equipment for decontamination in the field. The scheduling algorithm developed in this work is now a candidate for adoption in ANBACIS, the U.S. Army's decontamination decision support system.

Manoeuvre Warfare: Some Conditions Associated with Success at the Operational Level

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SUMMARY

This paper is concerned with the conditions likely to enhance the chances of achieving a breakthrough in modern manoeuvre warfare, and then of achieving success in the subsequent campaign. The study which it describes was based on some 159 battles, which a military historian assessed in terms of the success criteria just mentioned, and also rated in terms of some 32 qualitative factors. Of these factors it seems that the achievement of surprise; the employment of aggressive ground reconaissance; and the condition of air superiority enjoyed by the attacking side, were most strongly associated with success. The study also emphasised the positive relationships which existed between a high rate of terrain capture, a favourable loss ratio and the probability of a favourable campaign outcome. The paper concludes with some discussion of these results, and draws out some implications for the future of battle modelling at the operational level.

INTRODUCTION

In warfare the ultimate goal has always been to impose one's will on the enemy, and success has in the main depended on the manoeuvre and application, or threat, of force. Intermediate goals have thus included the destruction or neutralisation of enemy forces, and the attainment of key territorial objectives. It is natural, therefore, that much quantitative historical battle analysis has focused on the balance of attrition between one side and the other, and on the factors which may affect the rate of advance of the attacker.

It was some eighty years ago that Lanchester (1916) and Osipov (1915), probably independently, set out quantitative theories relating attrition rates to the numerical strengths of the opposing forces. Since that time there have been a number of studies which have appealed to historical battle outcomes in an attempt to confirm relationships of this kind (see, e.g., Osipov, 1915; Helmbold, 1961a, 1961b, 1964a; Willard, 1962; Weiss, 1966; and Hartley, 1991a). These studies have met with some success. However, the historical relationships which have been discovered are generally fairly weak and seldom seem to follow the precise formulations set out by Lanchester and Osipov. As Helmbold (1964b) has pointed out, victory in war appears in the main to be determined by factors other than numerical superiority. What these additional influences might be was the focus of attention of Dupuy. Dupuy (1984, 1987) surveyed a large number of historical battles, attempting to codify and quantify a host of human, environmental and technical factors and build them into a theory of combat. Although Dupuy's approach embraced many variables other than the numerical strength of the two sides, it was still force-centred: the additional factors were treated literally as force multipliers, affecting the expected balance of attrition. The final determinant of campaign success was seen as the balance of combat power: the sum of the killing power indices of the weapons of each side, times the product of the judged effectiveness indices for all other factors. Hartley's (1991b) approach was somewhat different. Taking Dupuy's data base and variables (some transformed in nonlinear fashion) he used stepwise multiple regression first to build up sets of linear equations predicting selected intermediate variables; and then to link these latter, plus some of the input set, to campaign victory.

Historical studies of advance rates have, if anything, been more numerous than those centred on attrition. A comprehensive survey of these studies has been conducted by Helmbold (1990a, 1990b). The sum of this evidence led Helmbold to the conclusion that accurate predictions of advance rates are not possible with the present state of knowledge. Still less do the surveyed studies help us to understand what sets a force in motion, what governs its speed once motion has started, and what causes it eventually to halt or reverse direction.

The present study is concerned with land warfare at the operational level. It has parallels with the work of Dupuy and of Hartley, in that it attempts to establish the conditions which facilitate campaign success, embracing variables other than just that of force. It also deals with manoeuvre, which, although a linked concept, does not necessarily equate to advance. Although manoeuvre has been a feature of land warfare over the centuries, the constraints which affect it have altered radically during the last hundred years or so. By the start of World War I the scale of mobilisation in major conflicts, coupled with the increased reach of modern weapons, has meant that an attacker is normally faced with a coherent and more-or-less continuous line of defence. It is first necessary to break through this defence in order to ob-

tain the room for manoeuvre. The alternative to a war of manoeuvre is one of attrition.

The dynamics of some breakthrough operations and subsequent campaigns are illustrated in Figure 1, which plots the areas taken by the advancing force as a function of time. One set of traces, typical of many Allied and US campaigns in World War II, shows a pattern of slow initial progress as the attacking force battles to penetrate an organised defence. The advance rate then accelerates once a breakthrough has been achieved, often with a tailing off thereafter. In the other set of traces, typical of German "'blitzkrieg"' operations, the initial phase of slow advance is virtually absent. The offensive campaigns have often been concluded before the forces in the first set have made their breakthrough. Accordingly, this study first attempts to establish the conditions associated with a successful breakthrough, and then those which may enhance the odds of achieving success in the subsequent campaign.

METHOD

The study was initially based on an examination of a sample of 100 operations and campaigns. Qualitative assessments of this sample, and of the further sample alluded to below, were made by a military historian, Charles Messenger (a small selection of whose published books is listed among the references). These battles were first categorised by him in terms of time taken to breakthrough and subsequent campaign outcome, as outlined below. He also produced judgements on some 32 qualitative factors, such as the achievement of surprise, visibility conditions, and the like. The association between this set of factors and judged battle outcomes was then assessed. (The ratings used in this study pertaining to air superiority were those produced by Messenger. However, they were subsequently compared with a set of ratings produced independently by Alfred Price, whose speciality is air warfare. Two of the several publications with which he has been associated are also listed among the references. A high degree of concordance was found between the Messenger and Price sets of air superiority ratings.)

Following this the original intention was to take a small subset of the qualitative factors — those which appeared to have the greatest impact on breakthrough and campaign success —

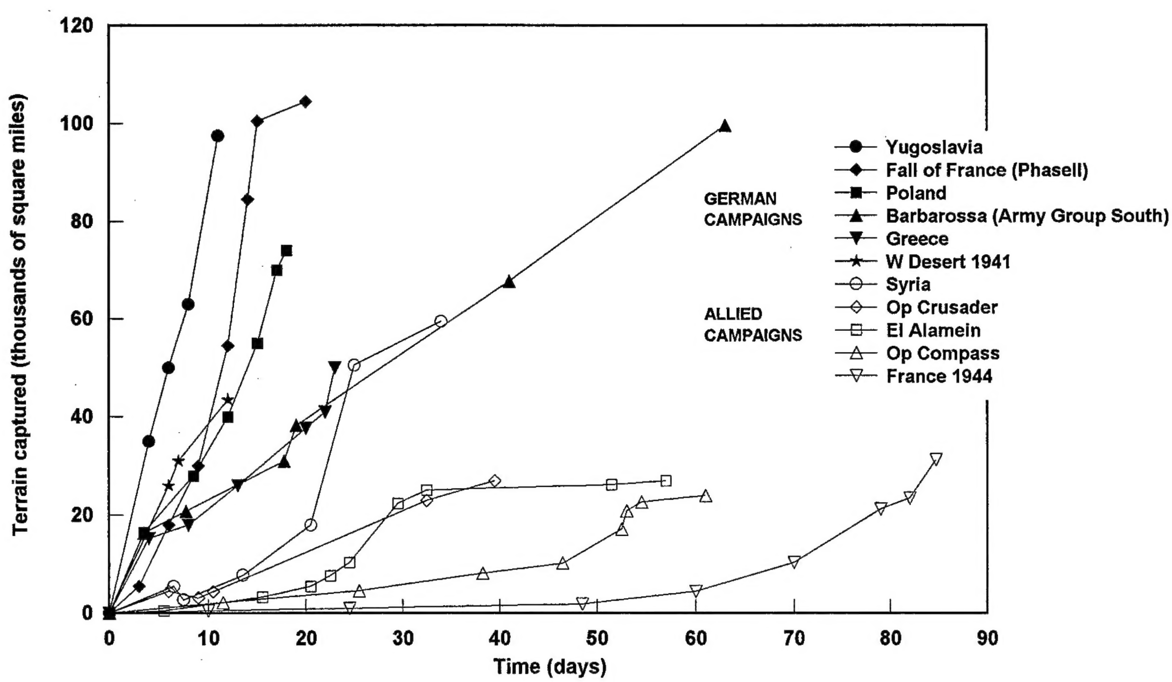

Figure 1. Some World War II German (filled symbols) and Allied (open symbols) campaigns compared in terms of terrain captured as a function of time.

Table 1. Battle sample

Initial study set (A)	N	Supplementary set (B)	N
World War I (1914–18)	10	World War I (1914–18)	24
Russo-Polish War (1919–20)	5	Russo-Finnish War (1939–40)	2
World War II (1939–45)	73	World War II (1939–45)	34
Korean War (1950–53)	3		
Arab-Israeli Wars (1956, 1967, 1973 & 1982)	8		
Gulf War (1991)	1		

and attempt to quantify them in a more rigorous and objective manner. This subset would then be combined in a final analysis with the more-easily quantified factors normally examined by operational research investigators: force numbers, frontages and terrain captured. As it so happened, the qualitative factors proved more difficult to quantify than was hoped and their effects seemed to outweigh by far those of the traditionally-emphasised quantitative factors. As a result:

a. The search for battles suitable for analysis was redoubled, and a supplementary set of 60 campaigns was located. This additional sample was analyzed independently from the first, acting as an informal '"cross-validation"' set. A very similar pattern of results was obtained in each case, and so the results quoted in this paper stem from the two subsamples combined.
b. Surprise emerged as probably the most important factor of all. Care was therefore taken to analyze this concept in more detail. As will be seen below, initial surprise was distinguished from subsequent surprise, and some consideration was given to the way in which surprise is related to the associated concept of '"shock"'.

Sample of Battles

The 160 battles studied covered actions in the wars shown at Table 1 above:

The main constraint in building up a large sample of campaigns was the availability of good source material. In some theatres (for example, the German Eastern Front in World War II) further operations could have been used, but the search was curtailed in the interests of maintaining some sort of a balance within the complete sample. In the event results were based on 159 battles from the full set of 160, as one did not fit into the broad categories developed for analysis. Table 2 is provided in order to give some idea of the range of campaign conditions contained within the combined sample.

Battle Outcome Categories

Four categories of breakthrough were established: immediate (I - breakthrough within

Table 2. Range of campaign conditions

Condition	5% of campaigns below	10% of campaigns below	10% of campaigns above	5% of campaigns above
Defence force size (k men)	10	13	400	500
Defence force density (men/km defence front)	40	200	2000	3300
Force ratio (attack:defence)				
Men	0.45:1	0.8:1	5:1	7.5:1
Tank + anti-tank*	0.45:1	0.8:1	17:1	α
Force density ratio (men)	1.0:1	1.5:1	25:1	45:1

* Excluding 17% of combined sample which had no tanks on either side.

half a day); quick (Q - breakthrough within the period of one half to two days); prolonged (P - final penetration takes more than two days); or failure to breakthrough (F). These could be combined with two categories of campaign outcome: subsequent success (SS) or subsequent failure (SF). The numbers in each combination of outcomes is shown in Table 3. The contrast of that proportion of campaigns successful after a breakthrough, 85%, with those in which there was no breakthrough, 16%, provides a basic indication of the value of a breakthrough as the start of a successful campaign.

Qualitative Factors

A descriptive list of qualitative factors rated by the military historian, together with their meanings, is appended to the paper as Table A.

As mentioned previously, surprise emerged strongly in the preliminary analysis as a factor of considerable importance. "'Surprise"' is defined as the confounding of expectations on the part of one side (usually the defender) by the actions of the other side. The split into "'initial"' (that achieved on Day 1 of the campaign) and "'subsequent"' surprise (that achieved thereafter) was made after the initial survey of results. "'Shock"' is one possible effect of surprise, and is defined as the stunning paralysis or debilitating effect of enemy action on individuals or an organisation.

Subjective ratings do cause problems in analyses of this kind, which will be alluded to once more in the closing stages of this paper. Assessments of surprise raise these problems in a particularly acute form. There are three different facets of surprise which are often confused, but which are in fact distinct:

a. The intention of (in most cases) the attacker to act in a way which, he believes, will not be expected by the defender.
b. The confounding of expectations on the part of the defender, whether or not this was the intention of the attacker.
c. The inability of the defender to respond appropriately, either through lack of time, poor appreciation, or because of his subjective reaction to this unexpected train of events (confusion or shock).

Facet (a) does not guarantee (b), and (b) does not guarantee (c). Furthermore, the symptoms of (c) can arise from causes quite other than that of confounded expectations (due to, for example, the sudden, and not necessarily unexpected, application of massive force). Facet (b) is the essential ingredient of surprise, and since it is a private state it is very difficult for the would-be assessor to be certain that it has occurred. It would be all too easy simply to infer (possibly absent) surprise from behaviour of type (c), in which case a strong link to unsuccessful defence would hardly be unexpected. The military historian involved with this study was very aware of the danger of unconscious biases, or "'halo effects"', of this kind. Steps taken to guard against them included the checking of conclusions against multiple sources. In this case "'shock"' was differentiated clearly from "'surprise"', and this does suggest that the latter was not simply inferred from the behaviour of the defender.

Table 3. Battle outcome combinations in study samples

	Outcome combination	Sample A	Sample B
F/SF	Failed breakthrough and subsequent failure	23	28
F/SS	Failed breakthrough, but with subsequent success	6	4
P/SF	Prolonged breakthrough and subsequent failure	4	2
P/SS	Prolonged breakthrough, but subsequent success	22	14
Q/SF	Quick breakthrough, but with subsequent failure	2	0
Q/SS	Quick breakthrough with subsequent success	10	7
I/SF	Immediate breakthrough, but subsequent failure	6	1
I/SS	Immediate breakthrough and subsequent success	26	4
	Not fitting these categories	1	0

RESULTS

Association between Qualitative Factors and Battle Outcomes

In this and all subsequent analysis we have examined two different splits of breakthrough outcomes. In what we have called simply "'breakthrough"', failure has been contrasted with success, however long it took to achieve that success. In what we have called "'rapid breakthrough"', failure or "'prolonged"' breakthrough has been contrasted with breakthrough which was "'quick"' or "'immediate"'. "'Campaign success"' is success in the overall campaign, whether or not it was preceded by a clear breakthrough. Table 4 lists the qualitative factors which were most strongly associated with these three criteria of battle success. In all cases the data were reduced to 2 × 2 contingency tables. We used the chi-square statistic to test for independence between the factors in each table. A significant chi-square statistic suggests strongly that the factors concerned are not likely to be independent. With one degree of freedom the values of chi-square corresponding to the 0.05, 0.01, 0.005 and 0.001 levels of statistical significance are 3.84, 6.64, 7.88 and 10.83 respectively. All the factors actually listed therefore achieve, as a minimum, the 0.05 level of significance with at least one of the three success criteria (and, by implication, those not listed fail to do so). Of course, statistical significance does not necessarily imply direct causation (and in particular, almost by definition, one would expect a rapid breakthrough to set the scene for subsequent surprise, and not the other way round). Still less can one guarantee that statistically significant factors are additive in their effects.

Taken over the campaign as a whole, judged on the ability to break through in the first instance and then to achieve the attack objectives, it seems that surprise ("'initial"' or "'subsequent"', sometimes associated with shock), aggressive attack reconnaissance and air superiority are most strongly associated with success. In contrast, the ability to achieve a **rapid** breakthrough seems to depend overwhelmingly on the first two of these variables, plus the commander's intention to do so. Although strongly associated with all three criteria, a more detailed analysis of "'shock"' is given elsewhere. In essence, though, those forces liable to show symptoms of "'shock"' when surprised were, as might be expected, more likely to be defeated in the subsequent campaign, and very much more likely to be broken through.

Further detailed analysis concentrated on the key variables mentioned at the start of the last paragraph (although this should not be taken to imply that the other significant factors were of no account). Table 5 shows how these three factors were associated jointly with the three battle outcome criteria (that of campaign success being irrespective of whether or not this was preceded by breakthrough). For this pur-

Table 4. Association between qualitative factors and baffle outcomes

Factor	Breakthrough		Rapid breakthrough		Campaign success	
	Chi-sq	Rank	Chi-sq	Rank	Chi-sq	Rank
Subsequent surprise	45.40	1	48.08	1	37.88	1
Initial surprise	37.23	2	47.40	2	10.22	10
Aggressive attack recce	26.73	3	16.08	5	32.20	2
Shock	22.71	4	33.88	3	17.48	5
Attack air superiority	19.94	5	4.42	7	23.16	3
Attack intelligence	19.08	6	4.39	8	12.12	8
Attack logistics	13.92	7	0.29	12	15.78	6
Attack C3	13.62	8	0.34	11	11.66	9
Mobility	11.17	9	6.27	6	17.61	4
Attack reserves	6.89	10	0.70	10	3.92	11
Attack special forces	4.03	11	2.66	9	12.80	7
Commander's intention	3.78	12	23.20	4	1.60	12

Table 5. Joint effect of three major factors on campaign outcomes

	Breakthrough	Rapid breakthrough	Campaign success
No factors present	0.0% (0/22)	0.0% (0/22)	9.1% (2/22)
One factor present			
Surprise	63.6% (7/11)	45.5% (5/11)	36.4% (4/11)
Aggressive recce	22.2% (2/9)	11.1% (1/9)	33.3% (3/9)
Air superiority	40.7% (11/27)	7.4% (2/27)	40.7% (11/27)
Two factors present			
Surprise + aggressive recce	83.3% (15/18)	55.6% (10/18)	66.7% (12/18)
Surprise + air superiority	90.9% (10/11)	54.5% (6/11)	63.6% (7/11)
Aggressive recce + air superiority	65.0% (13/20)	10.0% (2/20)	80.0% (16/20)
Three factors present	97.6% (40/41)	73.2% (30/41)	92.7% (38/41)

pose "'surprise"' has been taken as either "'initial"', or "'subsequent"' surprise, or both.

Post-Breakthrough Operations, Attrition and Campaign Success

If the infliction of casualties is one path to campaign success, boldness and speed of manoeuvre is certainly another. The author of the history of the British 11th Armoured Division, noted for its success in offensive operations in World War II, was at pains to coin a word, "irruption", which would capture the essence of this speed and boldness: "The word has been used ... to convey the impression of a force invading a region with speed and making a deep penetration inside it. Neither 'invasion' or 'penetration' would sufficiently indicate the pace at which the process was carried out".

In this study various quantitative measures of territorial success were examined, including rate of advance, area captured and so forth. The measure, I, which was finally devised to capture this sense of "irruption" was:

$$I = a / (f_a f_t)^{1/2}$$

Where

a is the total area captured (in square miles) per day,

f_a is the attack frontage (in miles), and

f_t is the theatre frontage (in miles).

This measure reflects the rate of terrain capture in units of miles per day, but scales it to the key force frontages. Above all, it seems better able to discriminate between successful and unsuccessful campaigns than do the other indices which were considered.

The summary statistics suggest that there is a regular pattern of association linking judged campaign success, speed of breakthrough, rate of "'irruption"' and loss exchange ratio. This association is shown in Table 6, where the loss exchange ratio, L, is measured simply in terms of attacker and defender personnel casualties. Clearly, the key to an advantageous loss exchange ratio is as rapid a breakthrough as possible. Table 3 (shown earlier) gives the sample sizes on which the summary statistics are based for each of the eight data points ("'immediate"', "'quick"', "'prolonged"' or "'failed"' breakthrough, with subsequent failure or subsequent success). For successful campaigns the quicker the breakthrough, the faster is the rate of irruption and the smaller is the loss exchange ratio. For unsuccessful campaigns it appears that the

Table 6. Average loss exchange ratios (L) and rates of irruption (I) as a function of campaign attributes

Breakthrough result	Successful campaigns		Unsuccessful campaigns	
	L	I	L	I
Immediate	0.42	14	0.9	0.25
Quick	0.53	10	1.2	0.4
Prolonged	0.71	7.5	1.7	1.2
Failed	2.4	4.5	2.2	1.5

rate of irruption is less for an immediate breakthrough which is subsequently thwarted than it is for quick, prolonged or failed breakthroughs; and that there is a steady, if gradual, trend in this direction. However, this limited advantage of territorial gain is bought at the expense of greater casualties. In the belief that one picture may be worth a thousand words, these points are also made in diagrammatic form in Figure 2.

Results from Other Studies or Using Other Data Bases

The present study has featured a number of combat dimensions other than that of force, and has emphasised the breakthrough as a prelude to successful manoeuvre warfare at the operational level. It seems sensible at this stage to gauge whether the results stemming from other studies or data bases are broadly consistent with those reported here.

Although few other studies seem to have concentrated on the breakthrough phenomenon, Dupuy did analyze 14 campaigns in an attempt to determine the factors contributing to success in this phase of the battle (Dupuy et al, 1976, abstracted in Dupuy, 1987). He concluded that "'. . . in order to achieve a breakthrough of a defense zone the attacker must have some sort of advantage in combat power"', which could be: a substantial preponderance of ground numbers or fire power (64%); combat effectiveness superiority (78%); superior mobility (78%); overwhelming air support (71%); surprise (57%); or some combination of these (100%). Bearing in mind the small numbers in Dupuy's sample, his conclusions seem roughly in line with those reported here. The Russians have also examined this topic. Radziyevskiy's (1979) findings, although not reported in a format familiar to Western analysts, also stress the importance of surprise.

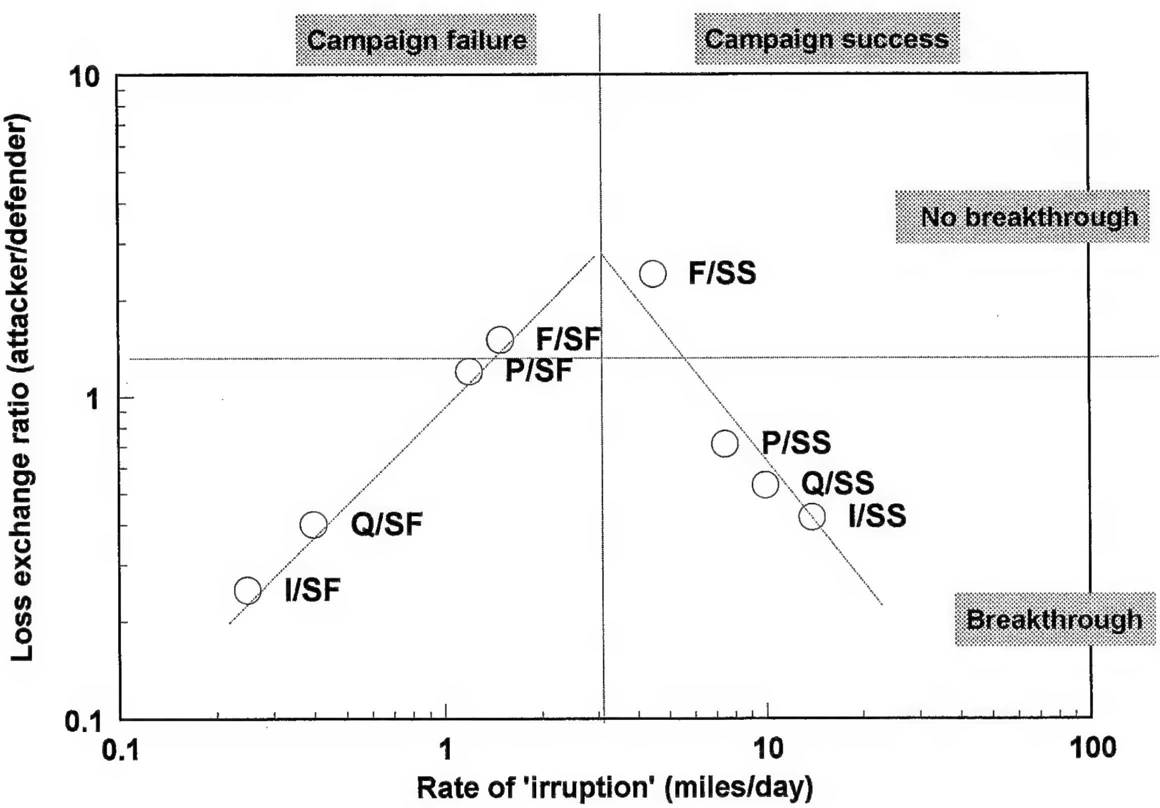

Figure 2. Diagrammatic representation of relationships between loss exchange ratio, rate of irruption and military outcomes (breakthrough category/campaign success).

The extensive data base assembled by Dupuy, and used by Hartley (1991b) in the regression analysis previously mentioned, did not include any information relating to breakthrough. Neither did the list of qualitative factors match those used in the present study. Nevertheless, to the extent that it was possible, we have attempted an analysis on parts of these data roughly paralleling our own, including in the sample only the 245 listed battles from the Russo-Japanese engagements in 1938 and subsequently. Of course, the standards of interpretation may differ for ostensibly similar factors, and the different characteristics of the two battle samples will themselves induce differences in the results. So far as theatres of war are concerned, the portion of Dupuy's data base which was extracted is more restricted than that used in the present study (so that, for example, there is only one battle from France in 1940, and none from Poland, Norway, Greece, North Africa prior to El Alamein, East Africa, Burma, Malaya or the Russo-Japanese war of 1945). On the other hand Dupuy's battles vary tremendously in scale, so that attack frontages, for instance, range from 0.5 to 1060 kilometres. Had the larger battles been included in the present study it is almost certain that they would have been subdivided into parallel operations. The salient points arising from this roughly parallel analysis are as follows:

Association between qualitative factors and battle outcomes. Four of Dupuy's qualitative factors have ostensible equivalents in the present study. The values of the 2×2 (one degree of freedom) chi-square measure of association between them and campaign success are (with those obtained in the present study being added in parentheses): air superiority, 19.61 (23.16); logistic superiority, 6.71 (15.78); intelligence advantage, 15.26 (12.12); and surprise (assumed to be initial surprise), 8.65 (10.22).

Post-breakthrough operations, attrition and success. Areas captured or lost by the attacking force were not given among Dupuy's statistics, and so the listed advance rates were used as a stand-in for our measure of "'irruption"'. If v is the recorded advance rate, then the correlation between the statistic sign(v) $\text{abs}(v)^{1/2}$ and the logarithm of the personnel loss ratio is -0.335. Similarly, the correlation between this statistic and campaign success is 0.556.

The results just quoted, and those in this study linking attrition, "'irruption"' and campaign success, highlight once again the possibility of a "'halo effect"' in subjective assessments. This was referred to previously during our initial discussion of surprise. It is quite likely that high rates of "'irruption"' and favourable loss exchange ratios will form part and parcel of any historian's perception of campaign "'success"'. Assuredly, they will also have coloured the judgements of "'victory"' or "'defeat"', and hence the resolve either to resist or submit, by those who were directly involved in the conflicts at the time. What is obvious is that, in this context, we should be especially cautious in applying our normal concepts of "'cause"' and "'effect"'.

DISCUSSION

By way of summary, Figure 3 depicts some main alternative ways that operational level campaigns may be structured. To avoid drawing in a plethora of arrows, only a few of the possible paths to ultimate success or failure have been sketched in. So, for example, initial surprise may still be followed by a failure to make a breakthrough; and so on. By and large, though, the arrows that are drawn in pick out the more likely of the alternative routes from each node. Similarly, of the different qualitative factors only initial and subsequent surprise are listed at the left of the figure. However, as this study has made clear, there are several other predisposing factors which may influence the transition probabilities between successive nodes. One analytic construct which has recieved much attention and evaluation in the past has been the so-called "'breakpoint"' hypothesis - a supposed lawful relationship between attrition levels on one or both sides and the attainment of ultimate victory or defeat. To the extent that this hypothesis does hold, it is only likely to do so if the final path to campaign outcome lies through attrition warfare. If, instead, it lies through manoeuvre the will to prevail or submit is far more likely to be influenced by spatial and geographical considerations.

The study reported here has been strictly circumscribed in its aims: to obtain qualitative measures of a number of factors which, on *a priori* grounds, seem likely to be of importance

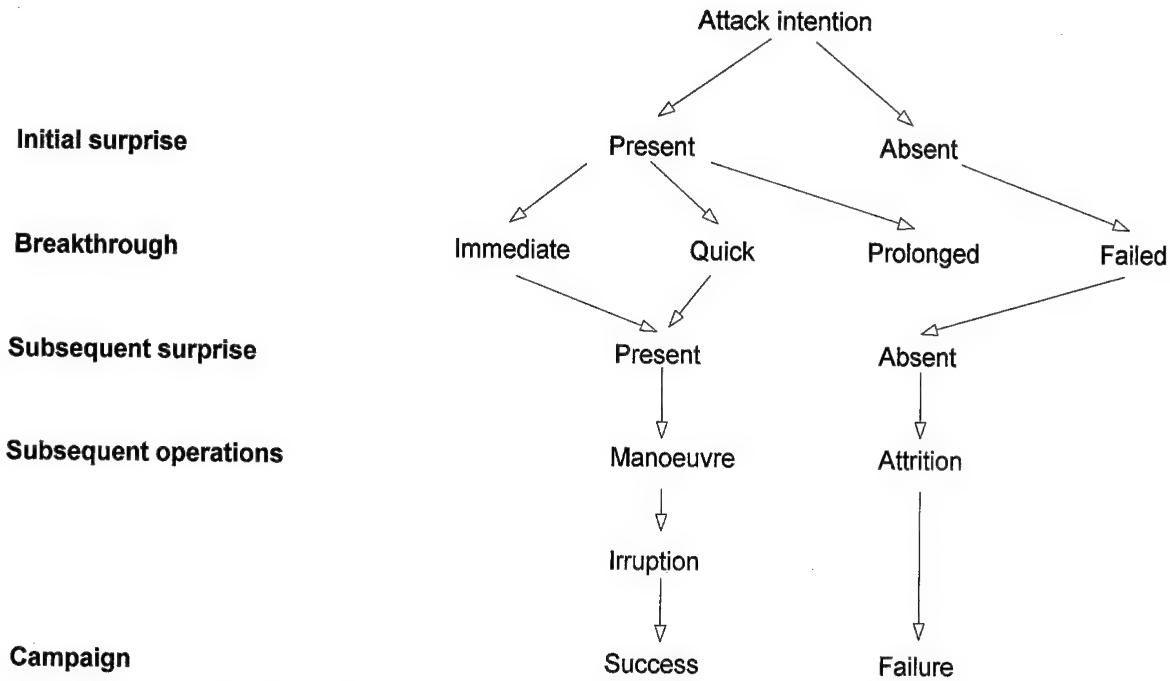

Figure 3. Schematic representation of alternative campaign structures.

in manoeuvre warfare at the operational level, and then to measure their degrees of association with judged military success. As mentioned earlier in the paper, the intention has always been to move on to a more quantitative modelling phase, in which a major matter of concern would be how these factors interact or compare with force, which latter seems to be the focus of attention for most military OR practitioners. To anticipate, results from this next phase of analysis suggest that, compared to the key factors identified here, the effects of force ratio are quite minor. But this in turn raises the question of how we should measure and define "'force ratio"', and takes us outside the scope of the present paper.

It seems likely that simply providing a list of measures of historical association between a general set of qualitative factors and an index (or indices) of operational success will do little to affect military OR practice, or to incorporate such factors into common modelling approaches. Studies akin to that reported here have certainly aroused a deal of interest in the past, and factors such as surprise have generally been recognised as being of potentially greater importance for military success than is force. But progress towards the goal of giving them their due weight in analytic studies will depend, *inter alia*, on building a proper description of the dynamics of manoeuvre warfare; on identifying in some detail the mechanisms by which the qualitative factors have their effect; and then by incorporating the one in the other. A first step is to ponder a little on the nature of the factors considered to be most important.

Surprise

The earliest military commentators, such as Sun-Tzu, placed great stress on surprise as a factor in warfare. If the emphasis then waned somewhat, it increased once more as defences grew stronger and as decisive manoeuvre became more difficult to achieve. As Fuller (1926) wrote between the two World Wars: "'To understand war (we) must exercise the nature of surprise in its thousand and one forms as it pursues its relentless course through history"'.

Any riposte to a military initiative must include the assessment of possible response options; the marshalling of military assets in time and space; and the employment of these assets effectively. Surprise could affect all three aspects adversely. Because the response options will have not have been prepared or considered in advance, they must be devised and evalu-

ated in stressful conditions and in haste, using only such information as is to hand. The planning and execution of orders will similarly be carried out under pressure. The initial deployment of the surprised force may not be well suited to the new situation, and so it may be difficult to bring all this force to bear on the enemy. The decisive conflicts may not then be on the ground or in the circumstances of the responder's choosing. Also, confusion and shock may seriously degrade military skills.

Surprise poses a special challenge for the would-be practitioner of military operations research. Even if one agrees with the opinions expressed above, turning these general precepts into specific modelling proposals and mechanisms is not a simple task. But there is a more difficult task still. Surprise has to do with the formation of human expectations and with how they may be confounded. The challenge for the analyst is thus to devise reliable techniques and procedures for gauging the expectations of each side in a putative battle, and for judging the extent to which these have been thwarted.

Air Superiority

The side possessing air superiority enjoys a means of applying force more or less at a time and place of its own choosing, and meanwhile can operate free from the threat of disruption and demoralisation due to air attack. Parallel analysis has shown that, historically, the defensive use of air assets to gain intelligence has had a particularly strong effect in decreasing the chances of breakthrough and of attack success. Denying the enemy this and other means of intelligence gathering has been an important role for air power. The struggle for air superiority seems set to remain a key factor in the increasingly complex information battle.

Aggressive Ground Reconnaissance

The gathering of intelligence is one obvious task for the ground reconnaissance assets of a military force. But the effects that these assets have on the final outcome seem to be greatly enhanced if they are used in an aggressive forward role. The quality of the information obtained then seems to be enhanced. The Russians have a term, *razvedka boyem,* which denotes gaining intelligence by fighting: provoking and evaluating an active response rather than simply noting apparent dispositions. But aggressive ground reconnaissance seems also to have had an effect in neutralising the defence recce; in seizing opportunities and key features, such as defiles or intact bridges; in deceiving the opposition as to the intended direction and nature of attack thrusts; and in disrupting rear areas and enemy HQs. These effects have been noted not just in battle records, but have shown themselves in studies of peacetime training exercises. Thus Goldsmith and Hodges (1987), as well as reporting the judged effect of the standard of reconnaissance on US NTC battalion-level exercise outcomes, noted that "'Experienced battalion commanders have claimed that good reconnaissance is worth two entire company teams to the task force"'.

Concluding Remarks

While suggesting in very general terms the mechanisms by which surprise, aggressive reconnaissance and air superiority may have their effects, these considerations by themselves do little to elucidate the fundamental dynamics of manoeuvre warfare. Nevertheless, they do suggest themes which almost certainly have a bearing on this matter. To be sure, all three of the factors considered make it possible to apply force to greater effect (or, probably more to the point, to make the opponent less effective). However, even more importantly, they appear to facilitate actions which will enable the field commander to achieve his military aims without plunging into major conflict. We can see one aspect of this in the phenomenon of "'irruption:': moving and acting in a manner which makes the attacking force difficult to pin down; which forces the defender into a responsive, rather than an initiating, mode; and which, other things being equal, reduces casualties. This leads one in turn to consider the role of force in the manoeuvre battle. Force is not used in warfare just to annihilate opposing force (as conveyed by the term "'potential-anti-potential"'), but more essentially to unbalance the other side. That being so, by simply concentrating on "'the correlation of forces"', and regarding factors such as those considered here as "'force multipliers"', one surely runs the risk of missing the essence of manoeuvre warfare.

Although this study has identified some factors which have in the past greatly enhanced the chances of achieving a breakthrough, these cannot be said to have been automatic triggers for advance. The rate, duration and extent of movement will depend on many things. The force itself must be designed for manoeuvre. The Soviet Operational Manoeuvre Group concept, much discussed just prior to the dissolution of the Warsaw Pact, is witness to the aspiration that a highly mobile formation could be designed and built, capable of operating more or less independently of anything that might happen in its rear. Given a breakthrough, the rate and extent of advance will depend in large part on the daring and resolve of the attacking commander. It was a common criticism of US and British commanders in World War II that they were too cautious, preferring to rely "' ... in the last analysis on firepower and sheer material superiority to win their battles, rather than on any concept of unbalancing the enemy"' (Ellis, 1990). A German report from Italy, quoted by Hastings (1984), put it: "'The conduct of the battle by the Americans and English was, taken all round, once again very methodical. Local successes were seldom exploited.... When an objective was reached, the enemy would neglect to exploit and would dig in for defence"'. Of course, provided that he is not demoralised, the defender will do all in his power to wrest the initiative from the attacker, and to impose his own desired pattern on events. Effective counter-manoeuvre will be that much easier if the attacker does not enjoy the major facilitating advantages identified by this study. It seems unlikely, therefore, that any simple function will predict the rate, duration and extent of an advance. Success in such a predictive enterprise will depend on the ability to model all the most important interactions of manoeuvre warfare.

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Table A. List of qualitative factors assessed by military historian (Charles Messenger)

Factor	Explanation
Initial surprise	Surprise achieved on Day 1 of a campaign.
Subsequent surprise	Surprise achieved subsequent to Day 1.
Shock	Appearance of paralysis or confusion in the defender.
Mobility	Mobility of attacker superior to that of defender.
Visibility	Good visibility on Day 1 of a campaign.
Day/night attack	The time at the start of the attack.
Natural obstacles	Present and influential in operations.
Trafficability	Good conditions for off-road movement.
Road density	High road density in the area.
Aggressive attack recce	Reconnaissance used boldly by the attacker.
Commander's intention	Attacker's intent to breakthrough as quickly as possible.
Attack preparation	Preparation for attack was careful and systematic.
Attack command experience	Attack commander experienced in this role.
Attack troops experience	Attack troops were experienced in combat.
Attack weapons	Attacker's weapons were appropriate and up-to-date.
Attack air superiority	Attacker had air superiority or supremacy.
Attack logistics capability	Attacker logistics fully capable of supporting operation.
Attack intelligence	Attacker had good intelligence of defence.
Attack special forces	Attacker employed special forces.
Attack C3	C3 well coordinated by attacker.
Attack reserves	Attacker had strong and well positioned reserves.
Attack artillery superiority	Attack artillery resources superior to those of defence.
Attack boundaries	Attacker manoeuvered outside own boundaries.
Defence type	Defence deployed in depth.
Defence preparation	Defence preparation was careful and systematic.
Defence command experience	Defence commander experienced in this role.
Defence troops experience	Defence troops were experienced in combat.
Defence weapons	Defender's weapons were appropriate and up-to-date.
Defence reserves	Defender had strong and well positioned reserves.
Defence special forces	Defender employed special forces.
Defence C3	C3 well coordinated by defender.
Defence boundaries	Defender attacked astride significant formation boundaries.

Exploring a Relationship Between Tactical Intelligence and Battle Results

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Operations Research Center and Department of Systems Engineering US Military Academy

This paper won the David Rist Prize at the 64th MORS Symposium as the best paper submitted in response to a call for papers.

INTRODUCTION

The United States Army intends to leverage greater combat power on future battlefields by skillfully exploiting information and information age technology. Of the various categories of battlefield information that may ultimately contribute to the generation of combat power, information about the enemy is clearly the centerpiece. Intelligence information provides the starting point and framework of combat operations planning. Knowledge of his enemy allows a commander to exploit enemy weaknesses and, therefore, maximize his own (friendly) combat power at the decisive point and time on the battlefield. Within each of its essential elements (maneuver, firepower, protection, leadership) the generation of combat power is predicated upon information about the enemy's location, intent, and will.

Intelligence information is, therefore, a valuable resource that must be aggressively acquired and effectively managed. Management of intelligence information begs for some measurable notion (in war-fighter terms) of its intrinsic value. While most people experienced in the operational art of combat would accept *a priori* that intelligence information has value; its value is, nevertheless, subjective, vague, uncertain and difficult to quantify.

This paper discusses efforts to quantify the value of information about enemy forces, weather, and terrain, that may be acquired through intelligence and reconnaissance activities. A focus of our work has been an attempt to demonstrate the feasibility of establishing links between the level of information a battlefield commander possesses about his adversary and the degree of success that commander enjoys in engaging his adversary in battle. Our interest is in the generic relationship between information level and combat success. Once such links are established, one could evaluate proposed changes in information acquisition tactics or hardware capabilities in terms of their expected impact on combat success. Additionally, this would, in principle, allow exploitation of game-theoretic and decision theoretic concepts to assist in exploring issues such as:

- at what points in time should a commander take certain actions, e.g., attack or wait for more information;
- what is an optimal allocation of information collection resources;
- what is the "value of information" in a given situation (how much should a commander be willing to "pay" for additional reconnaissance or intelligence); and
- what is the relative "cost effectiveness" of each information collection resource, and how well will it perform over time?

BACKGROUND

Our work in this area was motivated by a project MG Dave Robinson (as commander of the Army Aviation Center) suggested in 1993, to "develop a methodology for determining the 'value-added' of reconnaissance." Our initial work involved thinking in broad terms about functional processes that make up reconnaissance, and in developing a task analysis for the information gathering process (Strukel, et al (1993)). We also thought about approaches that might be used in measuring "value-added," and reported two we felt held good potential for success. One approach involved using Lanchester Models to measure the improvement in one combatant's performance as he evolved from area fire to aimed fire as a result of information gained through reconnaissance (Johnson (1993)). The other proposed use of combat simulation technology, in various ways. Initially, one could use constructive simulation models such as Janus to gain knowledge about sensor and platform performance in gathering information. This could be used to help design interactive experiments using distributed interactive simulation that would play the information fusion, assessment, dissemination and decision making aspects of reconnaissance, as well as the information gathering process (Barr, et al (1993)). Other notable work on the problem of measuring reconnaissance, reported by RAND, involved subjective assessments by experts (Cesar, et al (1993) and Veit and Callero (1995)) and analysis of data from the National Training Center (Goldsmith and Hodges (1987)).

The framework of many studies concerned with determining the value of intelligence information has been "value-added analysis," which seeks to determine the marginal return (sometimes measured in terms of "combat success") due to increased information about the enemy (Barr, et al (1993); Strukel, et al (1993); Veit and Callero (1995)). Several of these efforts explored the value of changing current Army reconnaissance in at least one of the following areas: 1) introducing new reconnaissance platforms or sensors, 2) changing the force structure of reconnaissance units, 3)

improving reconnaissance operations. Faculty and students in our department at West Point studied the value gained by adding Commanche helicopters or unmanned aerial vehicles to the reconnaissance effort (Carroll, et al (1993)).

In order to examine the nature of the relationship between intelligence information and combat success, we performed a modest experiment. Results of this experiment are reported below. A related experiment was conducted by CPT Pete Vozzo (Vozzo (1992)). Vozzo's experiment involved reenactment of a World War II operation known as "Operation Market Garden," using a commercially marketed board game. The game involves play at the Corps level by two adversaries, in a "double-blind" system in which neither player can see the other's deployment or movements. CPT Vozzo varied the rules of play of the game in six stages, to simulate increasing reconnaissance available to the attacking (Blue) player. He used only two plays of the game (with different players) at each stage of recon availability. Vozzo concluded there was clear evidence of increasing capability of the Blue player as his use of reconnaissance increased. Figure 1 shows a summary of Vozzo's results, in terms of decreasing battle duration and increasing level of success by the attacking Blue player. Vozzo apparently judged "success" subjectively in terms of whether the attacker was victorious, and if so, whether it was a "limited victory" or a "total victory."

THE EXPERIMENT

We performed a series of experiments with subjects playing the role of the Blue commander in simulated engagements of a Red force. We used the Janus model to simulate battles in which we controlled the amount of intelligence information possessed by the Blue commanders (subjects). The experimental design called for having subjects generate plans for an attack against a defending Red force. Each subject completed plans in five successive phases (see note 1). Additional information about the Red situation was given to subjects just prior to each phase. Thus each subject carried out planning repeatedly, with increasing information about the opposing force at each phase. These plans were implemented in Janus by the experimenters; the subjects were not allowed to observe the results of their plans. Each of the planned battles was iterated in ten Janus replications, and about a dozen measures of effectiveness (MOE) were computed with the resulting data. These MOE served as indicators of combat "success" with each battle plan. We report results for just three representative MOE in this paper.

Experimental Design

The design is fairly simple. We used six subjects, each at five information levels, with ten replicated Janus runs. Thus in the entire

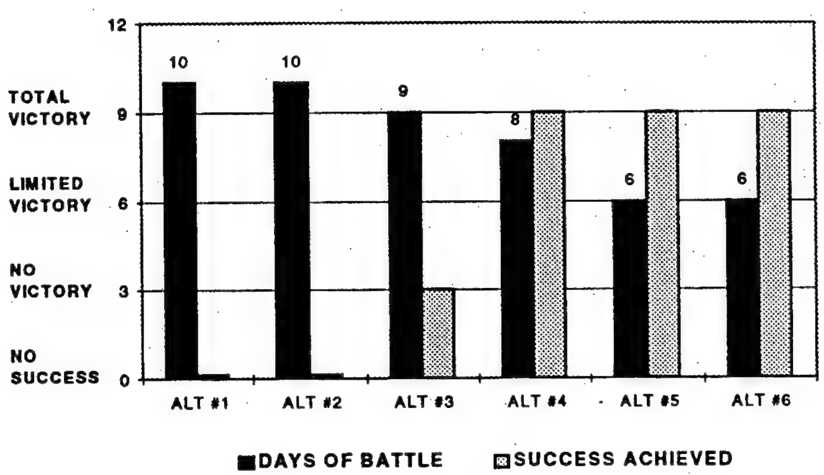

Figure 1. Contributions of reconnaissance as reported by Vozzo in his board game experiment (Vozzo (1992)). Days of battle (solid bars) and degree of success (shaded bars) are shown for six successively higher levels of reconnaissance capability available to the attacker.

experiment we obtained 300 values of each of the MOE. In addition we included the factor "category" which indicates whether or not a given MOE value was the first in the set of ten replications to which it belonged. This factor was included because the first battle fought with a given plan (that is, with a given subject at a given information level) was carried out in Janus with active interaction by the Janus operator (Sherrill). Once that battle had been fought, the subsequent nine replications were run in a "batch mode" of Janus, without active interaction by an operator. The interactive commands used in a first run were saved and replicated in the nine subsequent runs. We were concerned the first run, with active interaction by an operator, might tend to lead to better results than the subsequent "non-interactive" replications. Since Janus is a stochastic model, situations could arise in subsequent runs that were not present during the initial run. An active Janus operator can influence these situations. Hence, including the "category" factor with two levels allowed us to account for systematic differences between first and subsequent runs, and to test whether the effect is significant.

We expected there could easily be significant interactions between subjects and information levels. That is, we anticipated there would indeed be differences among subjects in the effects of varying information levels (so different subjects would have different information-battle success curves). Thus we included a "subject by information level" (denoted "Sub*Info") interaction term in the model used in the analysis of variance.

Learning

The experimental design we have described confounds learning effects with information level. Each subject formed his first plan at the lowest information level, his second plan at the next higher information level, and so on. We tried to limit possible learning by carefully precluding subjects from seeing the combat results of their plans in Janus. Nevertheless, it is probable some amount of learning about the terrain and the commander's own force did take place as the subject reconsidered the same scenario on the same terrain in five successive phases. It is, therefore, possible that part of the differences in battle success we observed with increasing information level could be due to learning by our subjects. It is also possible there was some increase in quality of plan implementation by the Janus operator over the course of the experiment. We tried to preclude this by performing many pilot trials of the experiment before record experimentation began.

Scenario

We used the Craig Gephardt attack scenario developed in conjunction with the Tactical Commanders Development Course, Ft. Leavenworth, KS. This is a Heavy Brigade attack scenario at the National Training Center. One Blue Battalion Task Force attacks west to east seizing key terrain from which to support the Brigade's Main attack conducted by a follow-on Battalion Task Force. Company sized remnants of a Motorized Rifle Regiment in hasty defense posture oppose Blue forces.

Subjects

Six members of the staff and faculty at the United States Military Academy agreed to play the role of task force commander during the experiment. In order to insure our subjects would employ current Army doctrine we screened potential subjects with the requirement that subjects be graduates of either the infantry or armor officer advanced courses. Graduates of these courses have planned heavy task force operations as part of course requirements. Though most of the faculty have even greater operational experience, this constraint ensured a lower bound on experience level. We conducted initial ("pilot") trials of the experiment with a "subject" from TRAC Leavenworth. The pilot trials allowed us to tune the experiment for record trials and, as mentioned above, attempt to advance our Janus operator up to the flat part of his learning curve.

Factor Of Interest

The factor of interest (control) in our experiment was the level of information available to subjects about their opponent. During the Army doctrinal planning process the commander's staff develops several intelligence products designed to deduce the enemy situation. Some of these products are: 1) modified

combined obstacle overlay (MCOO) (see note 2), 2) intelligence estimate, 3) doctrinal template, 4) situational template, 5) priority intelligence requirements, 6) reconnaissance and surveillance plan. The intelligence process is continuous and designed to provide the commander with an increasingly clear picture of the enemy's disposition, intent and will.

Developing a clear picture of the enemy, however, takes time. Seldom are we able to attain a "clear" picture of our opponent prior to conducting an operation. Additionally, operational requirements and unforeseen circumstances may dictate an early start of the operation. When the time schedule is moved up, we may be forced to use the current intelligence picture, however sparse. Afterward, we might ask, "How much more effective would we have been if we had developed a clearer picture of the enemy prior to combat?"

For our experiment we divided what we knew to be the complete set of information about the enemy into five subsets. We designed and sequenced the presentation of these information sets to correspond closely to doctrinally realistic increments of intelligence information available over time to a commander during the planning process. We next describe the information sets we provided subjects, numbered by their respective phase.

1) For the first phase we provided no information about the enemy. We gave subjects an abridged brigade operations order (OPORD), map and brigade graphics. The OPORD contained no information about the enemy; paragraph one (Situation) was restricted to information about friendly forces. We excluded the brigade fire support plan since it contained detailed target templates.

2) For phase two we gave subjects a complete operations order minus the brigade fire support plan. Additionally, the OPORD contained a complete intelligence estimate, MCOO sketch, and doctrinal template. During this phase we also provided our subjects with a tentative reconnaissance and surveillance plan and asked them to specify their priority information requirements (PIR) (see note 3). Commanders normally express PIR as questions. For example, "What obstacles are along route Rainbow?"

3) During phase three we added the brigade fire support plan. We also gave subjects a situational template and a scout spot report. The spot report contained some obstacle information and a direct fire contact report.

4) The information about the enemy we gave our subjects during phase four was simply the answers to their respective PIR. Within reason, we gave them exactly what they asked for.

5) We intended to provide nearly perfect information in phase five. Subjects entered the simulation laboratory and surveyed the enemy's positions, indicated by icons on a Janus display. Subjects could obtain any information they wanted, such as specific grid coordinates of enemy vehicles. Additionally, we provided them the enemy's fire support plan and fire synchronization matrix.

Procedure

For each phase of the experiment we gave subjects the respective information set. We required subjects to provide the following products of their battle planning exercise: 1) Task Organization, 2) Concept Sketch or Graphics, 3) Fire Support Plan, and 4) Synchronization Matrix. Once a subject turned in his plan he entered the next phase and we issued him the additional information set for developing his next plan. We then implemented the subject's completed plan in the Janus simulation model. Once a subject completed all five plans, we conducted ten Janus runs using each plan.

Measures Of Effectiveness

We captured data that supported computation of a number of MOE, including the three we report here: Loss Exchange Ratio (LER), Number of Combat Vehicles on the Objective (VO), and Combat Efficiency (CE).

LER is the ratio, Red Losses divided by Blue Losses. LER can give one insight into the amount of damage Blue inflicts relative to the amount he sustains (MacWillie (1992)). Though there are critics of this MOE, we include it here because it is frequently employed in practice. VO is a scenario specific MOE which measures mission success. In our application the mission was to seize a piece of key terrain (the objective) from which to support a friendly unit's attack. The level of mission success, therefore, depended upon the number of combat systems the Blue commander was able to place on the objective. Only systems that made it to the ob-

jective could accomplish the mission of subsequently supporting the friendly unit. CE is an extension of VO and is defined as VO divided by Blue Losses. In this regard CE measures mission success relative to losses sustained ("bang for buck"). The MOE VO and CE are included here because they illustrate different behavior patterns of response to increasing information, as we show below.

Measures Of Information Level

We considered three measures of the amount of intelligence information possessed by the Blue commander at each phase of the experiment. The simplest is the ordinal value of the phase identifier itself (the first phase has information level 1; second phase has information level 2, etc.). A second measure is based on the subjects' subjective assessment of the amount of information about their adversary they possessed at each phase. We collected this information from each subject after he had completed the final phase. We asked each subject to estimate information levels within the interval [0,1] by providing tic-marks on a printed line segment one unit long. These responses presumably give information levels relative to the "perfect information" available at the last phase of the experiment.

A problem with these first two measures of information level is their apparent close association with our specific scenario. As mentioned earlier, we hope relationships found with the methodology under discussion will prove to be useful as generic models linking information to battle success in a way more general than the specific scenarios from which they are derived. It appears, therefore, important to devise measures of information having more general characteristics. Thus we examined (and finally adopted) a third, apparently more general, measure of information, *entropy*. A comparison of the three approaches to measuring information level is summarized in Figures 2 and 3.

Entropy

Entropy as a measure of information was first developed by Shannon (Shannon (1948)) for application in assessing the information content of messages and the capacity of channels for transmitting messages; this area became known as information theory (Kinchin (1957)). While this has a connection with the concept of entropy used in thermodynamics (Sonntag and VanWylen (1966)), our application is more closely related to the information theoretic applications. We have previously applied entropy to the measurement of information gain due to reconnaissance (Barr, et al (1994 A); Barr, et al (1994 B)), and have used it to measure results of reconnaissance experiments conducted with combat simulation models (Barr, et al (1994 B); Carroll and Webb (1993)). Our experiences in carrying out the computations and in displaying information gain based on reductions in entropy as the recon battle progresses led us to conclude the measure has potential merit in our current application.

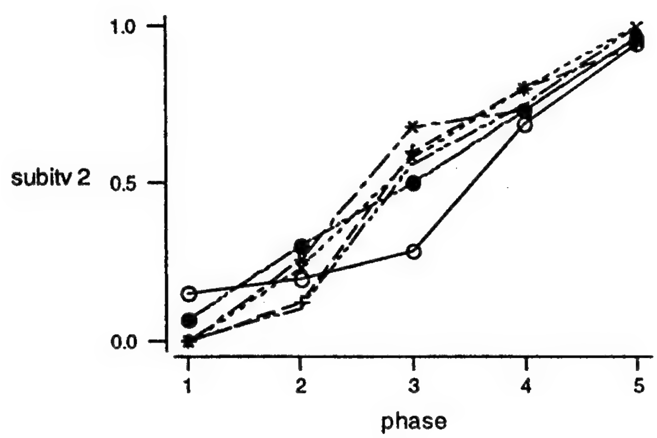

Figure 2. Plot of subjective self-assessments of information level versus phase number, by subject.

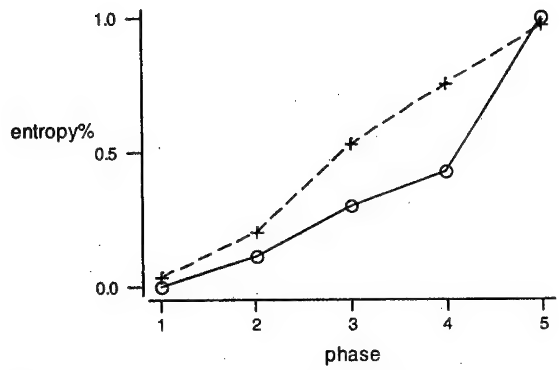

Figure 3. Plot of average subjective information assessment (dotted) and % entropy (solid), over five phases.

If a discrete system can be in state j with probability p_j; $j=1,2,\ldots,n$, the entropy e of the system is defined to be $e = -\Sigma p_j \cdot \ln(p_j)$ where the sum is over all states j for which $p_j > 0$. The entropy of a system is a measure of its "randomness." If a system can be in any of n possible states, the entropy of the system can range between 0 (when the exact state of the system is known) to $\ln(n)$ (when the state of the system has maximal randomness, which occurs when the system state is uniformly distributed). In the first case, where $p_1 = 1$ (say) and the remaining p_j's are zero, the sum above collapses to the single term $e = -1 \ln(1) = 0$. In the second case, the above sum gives

$$e = -\sum\frac{1}{n}\cdot\ln\left(\frac{1}{n}\right) = -n \cdot \frac{1}{n} \cdot \ln\left(\frac{1}{n}\right) = \ln(n).$$

COMPUTATION OF ENTROPY DECREASE

In our application to measuring the amount of information the Blue commander possesses about Red, we first represent Blue's knowledge of the location of each of Red's units of interest with a probability distribution of the unit's location. We describe briefly how this bivariate distribution was obtained for our experiment below; more detail is given in Barr and Sherrill (1995). Note the Blue commander does not generally know the number or nature of Red's units (by "unit" we mean vehicle or obstacle). We pose "what if" questions, such as, "If Red had a tank, what is the probability distribution of its possible locations?" The distribution of the possible location of such a unit within the area of interest to the Blue commander is a bivariate probability distribution over the area. Using the method described below, we compute the entropy of this distribution. This represents the degree of uncertainty Blue has about the location of the particular unit in question. We compute Blue's total entropy by summing the entropies of all the Red units. (This is valid under an assumption of independence; in Barr, et al (1994 A) we argue it provides a reasonable approximation of total entropy when unit locations are correlated.) The total entropy represents Blue's lack of knowledge about the location of Red units.

As the Blue commander receives intelligence and scouting information about Red's disposition, his probability distribution of location of Red armored vehicles and obstacles changes. In the beginning, without much information beyond a map of the area of interest, the locations of possible Red units are very imprecise, so the probability distribution is very broad with low values. Hence the entropy measure of Blue's lack of information is large. If Blue receives intelligence about Red's intentions and disposition, the probability distribution of location of possible Red units becomes somewhat less broad, and assumes higher values over certain (more likely) regions. Hence the entropy measure decreases from its earlier value. The amount of this decrease in entropy is a measure of the amount of information gained by the Blue commander.

In each phase of our application, we developed bivariate probability distributions representing our estimate of Blue's knowledge about the positions of Red units of two types, vehicles and obstacles. We computed the entropy of each distribution, summed these values over Red units, then found the decrease in this total entropy from each phase to its successor. We took the successive decreases in entropy from each phase to its successor to be our measure of the increases in information the Blue commander had about the Red force. Since we controlled the commander's access to new information at each phase, and it was the same for all subjects, we assumed we could estimate these distributions at each phase, and they are the same for all subjects. This enabled us to compute entropy reductions reflecting the receipt of new information. We used cumulative decrease in entropy as the values on the abscissa in several plots of battle success reported

below; for simplicity, we label this as simply "entropy decrease."

We did not attempt to measure our subjects' perceived distributions. Rather, we estimated probability distributions of Red unit locations for each phase by employing an expert. Our expert used the cumulative information set available at each phase, knowledge of Army doctrine, and knowledge of the terrain to construct the probability distributions. In this regard our expert played a role very similar to that of the intelligence officer preparing decision support products for the commander. The final product of our expert's estimate was what we called a "probability contour map" (PCM).

As its name implies, the probability contour map (PCM) partitions the total area of interest into sub-areas having given relative likelihoods of containing a Red unit, if such a unit were to exist in the area. In his expression of relative likelihood of Red unit locations, our expert first expressed the relative likelihood of containing a Red unit (given one exists in the area) as a categorical variable taking values: 1) very unlikely, 2) unlikely, 3) likely, 4) very likely. We represented these categories of likelihood numerically as 0, 1, 4, and 9 respectively. This numerical scale is a subjective assignment. We found there is little sensitivity of entropy decreases to changes in this representation; the process of estimating PCMs is described in more detail in Barr and Sherrill (1995).

Calculation Of Entropy

For our particular scenario, we developed separate PCMs for vehicles and obstacles, for each phase. Let R_0, R_1, R_4 and R_9 denote the regions over which a bivariate density corresponding to a given PCM has value proportional to 0, 1, 4, or 9, respectively, and let $A(R_0)$,. . .$A(R_9)$ be the areas of these regions. Estimates of these areas were obtained as follows. We estimated the areas of the portions of the four regions falling within each 1 km square, to the nearest .1 km^2, and then individually summed these estimates for each region type over the 140, 1 km squares comprising the 10 km by 14 km area of interest. We felt unjustified in attempting to estimate the areas of the four region types within any 1 km square to any resolution smaller than .1 km^2. Thus, there is some error in these estimates; a sensitivity analysis reported in Barr and Sherrill (1995) convinced us these estimates are sufficiently accurate for our purposes. In what follows, we refer to the imaginary .1 km^2 sub-regions of each 1 km square as "cells."

We determined a bivariate density function over the 10 km × 14 km area of interest so that:

- the integral of the density over the 10 km × 14 km area of interest equals 1.0;
- the density is constant over each region R_i; and
- the ratio of the density at a point in R_i to that at a point in R_j is b_i/b_j, where b_i and b_j are elements of the set {{0,1,4,9}}.

It follows that the density function value (height) at any point within R_i is

$$b_i \Big/ \sum_j b_j \cdot A(R_j); \qquad \text{for } b_j = 0,\ 1,\ 4,\ 9.$$

Now consider a discrete approximation of the for going density function, based on the .1 km^2 cells described above. We note the probability a particular Red unit is located in a given cell within region R_i is

$$p_i = (.1)b_i \Big/ \sum_j b_j A(R_j) = .1b_i/K,$$

where we let K denote the (constant) value in the denominator. The approximating mass function is defined to have values equal to the p's at the center points of the corresponding .1 km^2 cells. This mass function therefore is defined at 1400 points within the area of interest. Note it has fixed value p_i on $10 \cdot A(R_i)$ of these points.

Let us model the position of a given Red unit as having this discrete distribution over these 1400 cell centers. Then the entropy measure of Blue's lack of knowledge about this location is

$$e = -\sum_{i=1}^{1400} p_i \ln(p_i) = -\sum_{j=1}^{4} \frac{.1b_j}{K} \ln\left(\frac{.1b_j}{K}\right) 10 \cdot A(R_j)$$

$$= -\sum_{j=1}^{4} \frac{b_j A(R_j)}{K} [\ln(.1b_j) - \ln(K)]$$

$$= \ln(K) - \sum_{j=1}^{4} b_j A(R_j) \ln(b_j) / K - \ln(.1)$$

$$= \ln(K) - \frac{L}{K} - \ln(.1),$$

where $L = \Sigma_{j=1}^{4} b_j A(R_j) \ln(b_j)$.

It can be seen that the term $-\ln(.1) = \ln(10) = 2.3$ is related to our division of each square km into 10 cells, in the formation of the discrete approximation of the density of Red unit location. The approximation of the continuous density by a discrete mass function with "resolution" $1/10 \text{ km}^2$ introduces the constant term ln(10) into the entropy value. This may at first seem troubling, because the level of resolution employed in the discrete approximation step is somewhat arbitrary; we could have used cells of area .01 km^2 and gotten entropy values differing by a constant value involving ln(100), for example. However, our application involves taking the difference of the calculated entropy at two successive phases to be the information gain between the phases. The constant ln(10) adds out (as would the constant corresponding to any fixed level of resolution in the approximation) when the decrease in entropy is computed. Therefore, for our application, the level of resolution has only the minor effect of adding some noise in calculating entropy through inaccuracies in estimating the values of the $A(R_i)$, as mentioned above.

In addition to the area considerations, starting in phase 3 the Blue commander obtained information about the specific locations of Red units. Indeed, by phase 5, the Blue commander was able to view the positions of all Red units, as icons on the Janus display. The entropy associated with a known location derives from Blue's lack of knowledge of *which specific Red unit* occupies the known location. We used a combinatorial argument to determine the entropy associated with such lack of knowledge (Barr, et al (1994 A)). For example, in phase 4, the Blue commander learns of the location of six (out of a total of 22) obstacles. Given an obstacle is one whose location belongs to the set of discovered obstacle locations, it could "occupy" any one of these six locations with equal likelihood. Thus the entropy associated with such an obstacle is ln(6) = 1.792.

Combining Entropies By Conditioning

To combine entropies for targets among those with known locations (computed with combinatorial arguments) with entropies for targets with unknown locations (computed with area arguments), one cannot simply sum (or even use only a weighted sum related to taking an expected value). To see this, imagine drawing a target at random from the total set available, observing whether it "belongs" to the set of known locations, then computing its entropy conditionally, given the observation. Consider an indicator random variable I with values 0 (indicating the drawn target is in the set of known locations) and 1 (indicating it is of "area type"). Let $e_{T,I}$ denote the entropy associated with the location of a random target, determined by the compound outcome on I and location of the selected target, T, that is, with respect to the joint distribution of I and T. Similarly let e_I and $e_{T|I}$ denote the entropy of the distribution of I and the conditional entropy of target location, given the outcome on I, respectively. Then the entropy for the target is $e_{T,I} = e_I + E_I(e_{TI})$, where "$E_I$" denotes expected value with respect to the distribution of I. This can be established by a conditioning argument as follows:

$$
\begin{aligned}
e_{T,I} &= -\sum_{t,i} p_{T,I}(t,i) \ln(p_{T,I}(t,i)) \\
&= -\sum_{t,i} p_{T,I}(t,i) \ln(p_{T|I}(t|i)\, p_I(i)) \\
&= -\sum_{i}\sum_{t} p_{T,I}(t,i) \ln(p_I(i)) \\
&\qquad -\sum_{i}\sum_{t} p_I(i)\, P_{T|I}(t|i) \ln(P_{P|I}(t|i)) \\
&= -\sum_{i} p_I(i) \ln(p_i(i)) \\
&\qquad -\sum_{i}\left(\sum_{t} p_{P|I}(t|i) \ln(P_{T|I}(t|))\right) p_I(i) \\
&= e_I + E_I(e_{T|I})
\end{aligned}
$$

As mentioned above, in phase 4, for single obstacles, we have $e_{T|I=0} = 1.792$. Using area arguments, the entropy for an obstacle, given I = 1, is 3.572. The indicator variable takes value 0 with probability 6/22 and value 1 with

probability 16/22, so e_I = .586. Therefore the entropy for one obstacle is .586 + (6/22) · 1.792 + (16/22) · 3.572 = 3.672, and for 22 obstacles this gives entropy 80.79. A similar argument with vehicles in phase 4 gives entropy 186.75, so the total entropy for phase 4 is 267.54, as reported in Table 1.

A summary of the total entropy at each phase and the decrease in total entropy from the previous phase (representing information gain) is shown in Table 1. The rightmost column entries are actually cumulative entropy decreases; we used the label "entropy decrease" for simplicity here and in our plots.

Comparison Of Measures Of Information

The subjective assessments of information level as reported by the six subjects are shown in Figure 2. As can be seen, the subjective assessments were essentially proportional to phase number, so the plots fall close to a diagonal in the figure.

In Figure 3 we show how the average subjective assessment of information level compares with the entropy measure, for the five phases. The values of cumulative entropy decrease were scaled to "%entropy," by dividing entropy decrease values by the largest cumulative entropy decrease in our experiment, 74.24, to facilitate comparison.

DATA ANALYSIS

For each of the three MOE considered here, we performed an analysis of variance to determine the significance of the experiment factors (information level, subject, and category) and the interaction between information level and subject. The main purpose of this significance testing was to determine whether apparent differences in MOE means was due to changes in the factor levels, or was merely the result of chance variations in the Janus output from one run to another. Of particular interest is the test of the hypothesis that varying levels of information make no difference in the mean response for each MOE. To some extent the 'subjects' factor is a "nuisance factor," in that we are fairly sure different subjects will perform differently (hence no need to test whether this is true); however we want to remove this effect from the test about information levels, so as to improve the power of the latter test. A secondary purpose of performing analyses of variance was to demonstrate the experiment, as designed and conducted, generated definitive data in the sense that the tests have sufficient power to show significance of at least some of the factors under study. Thirdly, the fitted model might have some (limited) utility in facilitating predictions of combat success as a function of information possessed by the commander. Finally, the variance estimates associated with the analysis of variance can be useful in designing future follow-on or similar experiments.

Table 1. Total entropy decrease and information gain by phase of the experiment. Maximum entropy is based on a uniform distribution over 1400 cells.

Phase	Total Entropy	Information Gain	Entropy Decrease
Maximum	463.63		
1	299.23	164.40	0
2	290.79	8.43	8.43
3	277.03	13.76	22.19
4	267.54	9.49	31.68
5	224.98	42.56	74.24

Assumptions

We conducted diagnostic evaluations of the tenability of the major assumptions required in the analysis of variance procedure. These assumptions are:

- the data values for a given MOE are normally distributed (normality assumption);
- the data values for a given MOE all have the same variance (homogeneity of variance assumption); and
- the data values for a given MOE are statistically independent (independence assumption).

We also assume a "fixed effects linear model" (Box, et al (1978)). These assumptions are sometimes stated by asserting the response (MOE value), Y_{ijkl}, for subject i at information level j and category k in replication l is given by

$$Y_{ijkl} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \gamma_k + \epsilon_{ijkl}.$$

Here μ is the grand mean, the α's are subject effects, the β's are information level effects, the $\alpha\beta$'s are Sub*Info interaction effects, the γ's are category effects and the ϵ's are independent normally distributed "errors" (noise), having mean zero and constant variances.

Other assumptions, mentioned in the foregoing but listed here for completeness, are:

- there is no learning by subjects
- there is no learning by the Janus operator
- PCMs are the same for all subjects, and these can be estimated by a single expert.

Diagnostics

One data analytic diagnostic procedure involves examination of the residuals for a given fitted model. (A residual is the difference between an observed value and the corresponding mean value predicted by the fitted linear model in the analysis of variance.) Such analysis can often detect when one or more of the above assumptions is untenable for a given MOE.

We were particularly concerned with the homogeneity of variance assumption, because experience has shown there is often a link between the mean response of certain MOE such as LER and the corresponding variance. Such a link between means and variances would invalidate the homogeneity of variance assumption. It is well known the analysis of variance procedure is quite robust with respect to departures from normality, but it is not robust with respect to heterogeneity of variance (sometimes called "heteroskedasticity") (Box, et al (1978)). We were not very concerned about the independence assumption, because the experiment trials were conducted in a way to ensure that independence would reasonably be met.

A first notion of possible heterogeneity of variance for a given MOE can be gained from examining a plot of the residuals for that MOE against the mean values predicted by the fitted model. Ideally the plot will represent a horizontal cloud of points without trend and with fairly constant spread. In several cases, we observed residual plots that appeared cone-shaped, with larger vertical spread of residuals for factor level combinations giving larger predicted means. An example, for the case of the MOE "loss exchange ratio" (LER), is shown in Figure 4.

In the figure it can be seen that there is an apparent link between the mean response (on the abscissa) and the variance in response (as indicated by the spread of values in the vertical direction). This suggests strongly the homogeneity of variance assumption is untenable for LER. Since the analysis of variance process is sensitive to such heterogeneity of variance, it is necessary to modify the analysis method in this case.

We further examined the nature of the link between mean LER and the variance in LER as follows. We prepared a plot of mean values versus standard deviations within the 30 cells of the design matrix. Thus each (mean, stan-

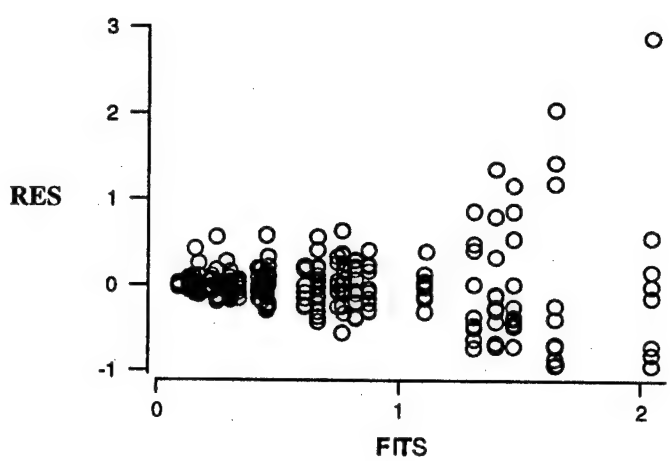

Figure 4. Plot of residuals ("RES") from fitted linear model against "fitted" (predicted) values ("FITS"). Note the cone-shaped pattern of points, suggesting the homogeneity of variance assumption is untenable.

dard deviation) pair is based on 10 independent observations of the LER measure. Such a plot is often referred to as a "x-bar-s plot." In the case of LER, the x-bar-s plot in Figure 5 reveals a probable linear relationship between the standard deviation and the mean of LER.

It can be shown (Barr and Zehna (1983)) that in this case, the transformed variable log(LER) will have (approximately) homogeneity of variance. In this case, the log-transformation of the LER data is called a "variance stabilization transformation."

We performed the analysis of variance on the stabilized LER data, that is, on the log(LER) data. This analysis should provide useful insights into the significance of the experiment factors using analysis of variance. The variance stabilization made the homogeneity of variance assumption tenable for this analysis of variance, as demonstrated in a plot of residuals against predicted log(LER) values (see Barr and Sherrill (1995)). The result of this analysis of variance for log(LER) data is shown in Table 2.

It can be seen in Table 2 that the factors Subject ("Sub") and Information Level ("Info") are highly significant, as is the Sub*Info interaction. We expected to encounter significant interaction between subjects and information level. It is due to the differing ways the six subjects were able to exploit the information available to them at the five phases of the experiment. The nature of this interaction for the LER measure is shown in the plot of LER means against phase number, by subjects, shown in Figure 6. In the figure it is apparent that the various subjects performed at substantially differing levels, in terms of LER, over the five phases of the experiment. We note the category factor, included to check whether there is a significant Janus operator effect in the first run made with each plan (as compared with the subsequent replications for the same plan, made in "batch mode") is not significant. We conclude there is no need to be concerned about systematic first run to subsequent replication differences for LER The plausibility of the normality assumption for the log(LER) analysis of variance was supported by examination of a histogram of residuals that displayed a bell-shaped pattern of frequencies (see Barr and Sherrill (1995)).

Even though there are individual subject differences over information levels, it is possible to see there is also a general pattern of increase in LER over the early phases, with lesser or no increase over the final phases. Therefore, it is reasonable to infer a general shape of LER response as a function of information level. Because one subject appears to have performance markedly different from most of the others, we estimated the over-all (subjects) performance profile by the median LER response at each information level. A smoothed plot of median LER against entropy decrease is shown in Figure 7.

Figure 8 shows box plots for LER, by level of information gain. The boxes in the figure are centered at the median of the LER data for the given information level, with the interquartile range of values shown by the height of the boxes. The pattern of boxes suggests the shape of the relationship between information level

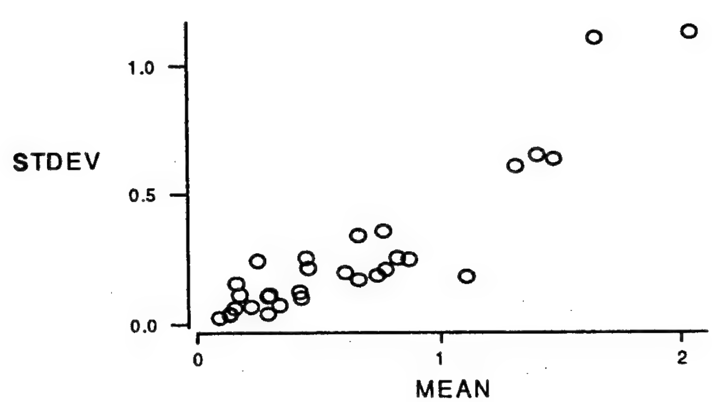

Figure 5. Plot of standard deviations versus means for 30 cells of the experimental design matrix. Note the linear relationship between the sample mean (x-bar, on the abscissa) and the sample standard deviation (s, on the ordinate).

Table 2. Analysis of variance summary for log(LER). The significance values shown in the column under "P" show the probability a second independent test would give an F-ratio as large as the one computed here. It is thus a measure of the degree of compatibility of the data with the hypothesis of no effect due to the factor.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Sub	5	50.9767	50.9767	10.1953	56.05	0.000
Info	4	111.1753	111.1753	27.7938	152.79	0.000
Sub*Info	20	54.5165	54.5165	2.7258	14.98	0.000
Category	1	0.3194	0.3194	0.3194	1.76	0.186
Error	269	48.9344	48.9344	0.1819		
Total	299	265.9224				

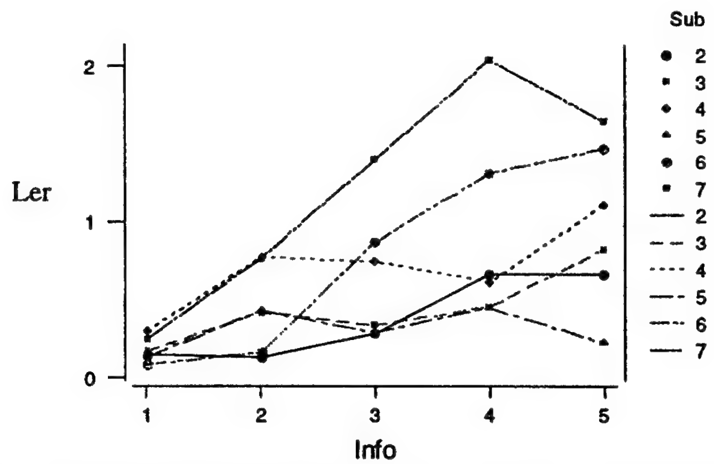

Figure 6. Plots of Mean LER versus information level(phase number), by subject.

and median LER, together with a "confidence band" about the medians.

We carried out analyses for each of the remaining MOE similar to those reported above for LER. The analysis of variance summary tables for VO is shown in Table 3 and a plot of median VO versus information gain is shown in Figure 9.

Note in Table 3, the factors Sub and Info (as well as Sub*Info interaction) are highly significant. The nature of the interaction is illustrated in Figure 10.

In this case, the factor category is also significant, suggesting there is a Janus operator effect between runs conducted with operator involvement and replications in batch mode. Indeed, over all subjects and information levels, the mean number of vehicles on the objective is 21.4 (with standard error 1.09) for first runs and 14.00 (with standard error 0.36) for subsequent replications in batch mode.

We believe this difference is attributable to actions at obstacles. Some vehicles were trapped behind obstacles in subsequent runs that were not trapped in the initial run. For example, in the initial run of a battle (where the interactor actively participates) the interactor deploys vehicles and breaching equipment to reduce and penetrate obstacles as per the subject's plan. At the command of the interactor, tanks may follow an engineer vehicle such as an armored combat excavator (ACE) through the obstacle. As stated earlier, these interaction commands are saved and replicated in subsequent runs. In subsequent runs however, the ACE may be destroyed (due to the stochastic nature of Janus). Consequently, the tanks will be trapped behind the obstacle and never make it to the objective even though they may survive the entire battle.

The plots shown in Figures 9 and 10 suggest there is not substantial improvement in the

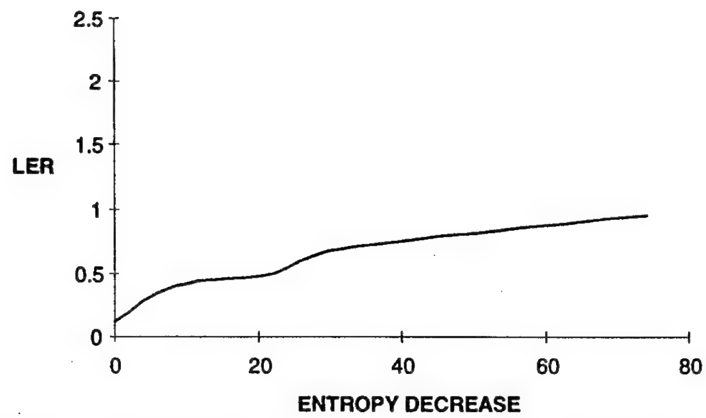

Figure 7. Plot of median LER against cumulative entropy decrease.

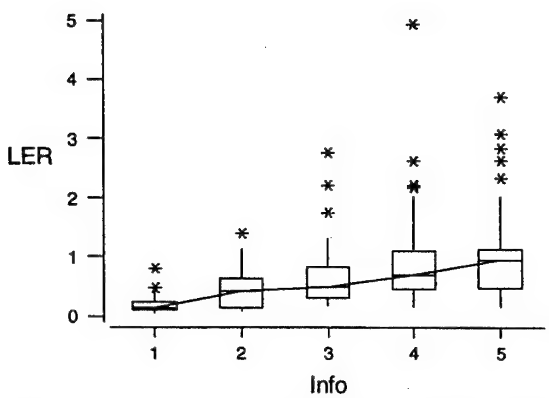

Figure 8. Box plots for LER, by level of information gain (phase number).

ability of the Blue commanders to achieve success in the mission objective, as information level increases beyond that available at the third phase. However, there is continuing decrease in blue losses over the entire span of five phases (Figure 11).

This suggests that a commander does not require information beyond a moderate level in order to achieve mission success, but he can do so at less cost in blue casualties with more information beyond the moderate level. We defined the MOE combat efficiency (CE) as the ratio V0/(Blue Loss), to measure the "efficiency" with which the Blue commanders achieved their objectives. The analysis of variance summary for this MOE is shown in Table 4, and a plot of median CE versus information gain is shown in Figure 12.

We observe in Table 4 that Sub, Info, and the Sub*Info interaction, are all significant. The nature of the interaction is illustrated in Figure 13.

CONCLUSIONS

Our study used a TRADOC-developed scenario within a constructive simulation model. We therefore had the opportunity to incorporate realistic terrain and weather conditions, to employ current Army doctrine, to conduct repetitive independent runs in order to increase the quality of inferences and provide estimates of error, and to capture data supporting several measures of effectiveness.

We were able to estimate links between information level and combat success. We found there is a point of diminishing returns, for most MOE, as information available to the Blue commander increases. However, this seems not to be the case for resource consumption-related MOE. For example, increasing information across the entire spectrum allowed the Blue commander to accomplish his mission while suffering decreasing losses. In summary, as information increases toward its maximum there is a point of diminishing (or even decreasing) returns in mission success MOE, but monotone improvement throughout the range for resource consumption MOE. This suggests a commander can achieve mission success with a moderate amount of information, but he can do so more "efficiently" (fewer casualties, lower fuel and ammunition consumption) with more information. This appears to be consistent with CPT Vozzo's results in his board-game experiment, where "success achieved" is a mission success MOE and "days of battle" is a resource consumption MOE (Figure 1).

Table 3. Analysis of variance summary for number of vehicles on the objective (VO).

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Sub	5	9667.7	9667.7	1933.5	53.93	0.000
Info	4	14335.2	14335.2	3583.8	99.96	0.000
Sub*Info	20	12465.4	12465.4	623.3	17.39	0.000
Category	1	1477.0	1477.0	1477.0	41.20	0.000
Error	269	9643.9	9643.9	35.9		
Total	299	47589.2				

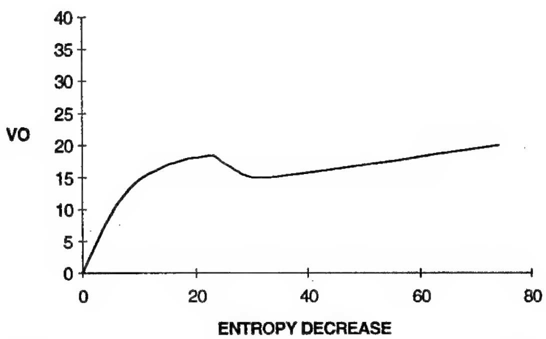

Figure 9. Plot of median #Vehicles On The Objective (VO) versus cumulative entropy decrease.

The relationships we present between information level and battle success appear to have potential utility in allowing one to estimate the impact of proposed changes in intelligence products or reconnaissance sensors, platforms or tactics. If one can evaluate the information gain associated with introducing new hardware or tactics, relative to a baseline status of information, one can estimate the impact of these changes in operational (war-fighting) terms, using links such as those we have developed. Moreover, this could open a way to further exploit methods and theory related to decision making and conflict.

Our results demonstrate that determining such information-combat success links is feasible and show an approach for establishing them. Further experimentation would help make the specific links we report more exact, and allow examination of the scope of their applicability through experimentation with changes in a variety of parameters such as scenarios, force sizes; and experience level and training of the decision maker. Variance estimates obtained with data from our experiment can be useful in the design of future related experiments, for example in sample size determination.

The use of entropy decrease to measure information gain through intelligence activities or reconnaissance operations seems to have excellent potential. Some theoretical developments, including a characterization theorem, are presented in Barr and Sherrill (1996). The theoretical properties of information gain, together with results from several experiments, lead us to infer the concept has a generic qual-

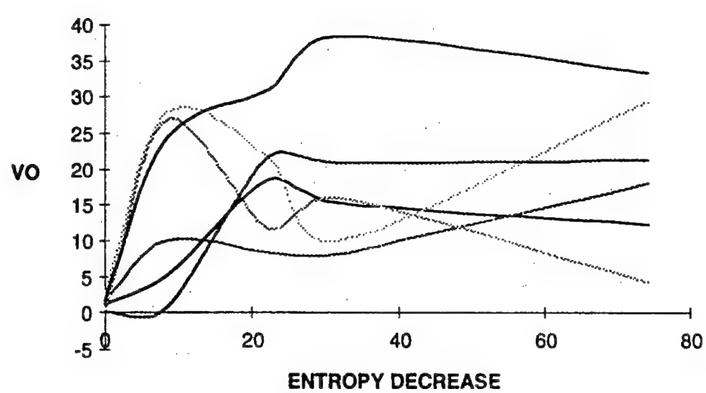

Figure 10. Plot of mean VO versus cumulative entropy decrease, by subject.

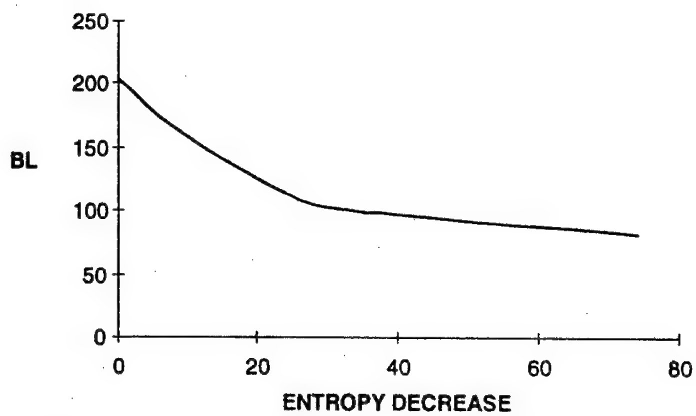

Figure 11. Plot of median Blue Losses (BL) versus cumulative entropy decrease.

Table 4. Analysis of variance summary for combat efficiency.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Sub	5	8.51347	8.51347	1.70269	33.05	0.000
Info	4	3.90035	3.90035	0.97509	18.93	0.000
Sub*Info	20	5.63709	5.63709	0.28185	5.47	0.000
Category	1	0.05199	0.05199	0.05199	1.01	0.316
Error	269	13.85985	13.85985	0.05152		
Total	299	31.96275				

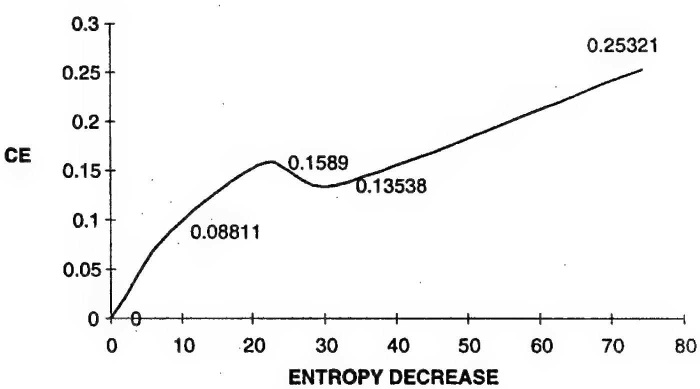

Figure 12. Plot of median Combat Efficiency (CE) versus cumulative entropy decrease.

ity. If so, the behavior of the measure suggest interesting fundamental properties about information with operational implications for military forces. More work in this direction seems justified.

We are currently working on an implementation of the measure in a Janus postprocessor (Sherrill and Barr (1996)), that will make information gain available as an MOE for analysts using this combat simulation. The method appears to have potential for larger-scale applications in combat simulation, field testing and, possibly, as an embedded element of future command and control systems. The computational burden of such an implementation is dependent mainly on the number, n, of cells in the

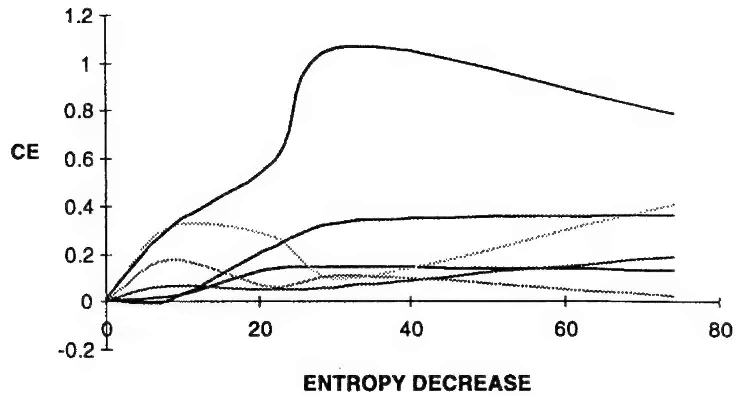

Figure 13. Plot of mean CE versus cumulative entropy decrease, by subject.

terrain map, and to a lesser extent on the number, m, of sensors involved in the search for enemy assets. Automating the measure requires line of sight computations; worst case occurs when all m sensors can range all n terrain cells. The algorithm's complexity is, therefore, in O(nm). Overall, the computations involved are not heavy, and control of n may be exercised by choice of scale.

Finally, we believe there may be applications of some of these ideas to many facets of managing information processes, such as optimally allocating information gathering resources, determining the marginal value of information and timing decision points, assessing the operational value of alternative information levels or processes, and training decision makers to properly use information, particularly in cases of very high information levels.

NOTES

[1] A "phase" is a portion of the experiment in which a given level of information is available to a subject.

[2] The MCOO is a terrain analysis product that categorizes the entire area of interest by trafficability. Developing the MCOO is a joint effort by the engineer and intelligence staff officers. The MCOO highlights key terrain, obstacles, and possible enemy avenues of approach.

[3] Priority Intelligence Requirements are defined in FM 34-2-1 as, "what the commander must know about the enemy, weather, and terrain to accomplish the mission."

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Illness Incidence During Military Operations as a Soft Operations Research Factor

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INTRODUCTION

Military Operations Research has witnessed an accelerated evolution in its breadth to include a host of variables which in years gone-by would have been considered outside the realm of operations research (OR). These factors, largely subsumed under the umbrella term "soft factors", include variables related to human performance – variables such as training, morale, and leadership. Typically, soft OR views the individual as an extension of the weapon or weapon system. The individual is viewed as a "man-in-the-loop" and attempts are made to quantify the effects of cognitive and / or emotive functioning on the individual's ability to operate the weapon system.

Often in ground-based combat operations, however, success is not measured by the performance of man and machine in concert but rather by the ability of an infantry company or battalion to seize territory or defend positions. In this type of scenario the "system" being evaluated is the combat unit.

In addition to personnel who are wounded and killed, the conditions of ground combat also yield sizable numbers of soldiers who become non-effective because of disease and non-battle injuries (see, for example, Hoeffler, 1981; Graham, 1991; Sharon, 1993; and Withers, 1994). The health of the combat unit, then, also constitutes an OR factor which needs to be understood to gain a fuller understanding of combat unit effectiveness. The present investigation explores the health of combat and support units during various ground operations and quantifies the rates of disease and nonbattle injury (DNBI) incidence.

COMBAT VS SUPPORT TROOPS

Combat status of the troops may impact the rates at which DNBI will be incurred. The most forward-deployed units, typically combat units as opposed to support troops, are exposed to the least hygienic conditions. Not only may combat troops operate in generally unhealthful environments, but they are also much less likely to have opportunities for bathing of anything more than a rudimentary nature. Further, dietary intake may be compromised and opportunities for sleep may be fewer among combat troops than among support troops. All of these factors may contribute to differences in DNBI incidence between combat and support troops.

BATTLE INTENSITY

The intensity of battle may also affect the health, and therefore the functioning, of the combat unit. Wartime DNBI incidence consists of three major components: diseases, non-battle induced injuries, and battlefield stress casualties. Combat stress is not a new phenomenon and there are numerous documented accounts of soldiers being incapacitated by the psychological demands of war (Manglesdorff and Furukawa, 1982; Manglesdorff, King, and O'Brien, 1983; Manglesdorff, King, and O'Brien, 1984. There is also considerable evidence that stress can impair the immunological system's ability to resist disease (Ader, 1990) which may also contribute to elevated rates of disease among troops engaged in hostile operations.

METHOD

Disease and nonbattle injury incidence data were extracted for combat and support troops from administrative and medical records of selected military operations spanning four decades. Information was collected on the numbers of DNBI sustained as well as the unit strengths, the lengths of treatment, and the types of facilities in which the casualties were treated. Rates were computed per 1000 strength per day. "Presentation" rates represent the incidence of all DNBI cases requiring treatment at Echelon II (medical battalion) or greater; "admission" rates are based on a subset of presentations which required treatment lasting three days or more. Outpatient visits, which encompass non-admission cases seen at clinics, dispensaries, etc. and which are then returned to duty or referred to the next level of care, are not the subject of the current investigation.

Okinawa Data. The assault on Okinawa was a three-month operation of generally high intensity lasting from April through June of 1945. U.S. Marines involved in the assault included the 1st Division, the 6th Division, and, in the closing stage, the Eighth Marines from the 2nd Division. Combat troop data were extracted from 36 company-level and 38 battalion-level muster rolls and represented 471,936 mandays in April, 408,224 mandays in May, and 343,990 mandays in June.

Additionally, data were extracted for a number of other units that participated as combat support elements. Supporting units

included two medical battalions, two engineering battalions, two pioneer battalions, two motor transport battalions, two amphibian truck companies, two service battalions, two assault signal companies, and a headquarters battalion. Support troop data represented 146,418 mandays in April, 274,912 mandays in May, and 229,568 mandays in June.

Korea Data. Data were extracted from Unit Diaries of U.S. Marine combat and support units deployed to Korea during 1951. A five-month period of data (February to June 1951) was extracted for randomly selected companies from infantry battalions of the 1st Marine Division, which saw a range of combat intensities. These data represented five Headquarters & Service Companies (H&S), four Weapons Companies, and 11 Rifle Companies that were elements of the 1st and 5th regiments. The total mandays represented by these 20 companies were 625,209.

Additionally, data were extracted from Unit Diaries of 35 companies providing support to the infantry troops during the same time period. These 35 companies represented troops from a medical battalion, engineer battalion, ordnance battalion, signal battalion, shore party battalion, motor transport battalion, service battalion, headquarters battalion, and the Marine Air Wing service squadron. The total mandays represented by the support troops over the five-month period were 1,134,036.

Vietnam Data. Data were extracted from Unit Diaries of eight randomly selected companies from infantry battalions of the 1st Marine Division. A four-month period from May through August, 1968 was chosen for analysis because its June mid-point represented the peak of U.S. Marine involvement in Vietnam in terms of troops deployed. The companies analyzed were six rifle companies and two Headquarters & Service companies from the 1st and 5th infantry regiments; the total mandays of these eight companies were 205,186.

Falklands Data. Data detailing DNBI incidence among the United Kingdom Amphibious Force (UKAF) were extracted from OPERATION CORPORATE medical logs/records maintained during the 1982 Falklands Conflict. These data included the numbers of disease/nonbattle injury cases as well as the treatment facilities and unit strengths during the 25 day ground operation occurring from May 21 through June 14, 1982. The total number of mandays represented by the UK ground forces during OPERATION CORPORATE was 168,609. Because the logistics troops of the UKAF represented a small percentage of the total ground force (10%), rates were not separated for combat and support units.

DESCRIPTIVE ANALYSES

Figures 1–6 are graphical depictions of the DNBI presentation rates juxtaposed with casualty incidence for combat and support troops in Okinawa and Korea, and for combat troops alone in Vietnam and the Falklands. Casualty rates comprise both wounded-in-action (WIA) presentations and killed-in-action (KIA). These figures highlight the dynamic nature of battlefield operations and illustrate the point that the disease/nonbattle injury incidence of battlefield units varies with status of troops (combat or support) as well as with the intensity of combat. These variations, in turn, can have a tremendous impact on the unit's operational effectiveness. Figure 7 displays the mean DNBI presentation and admission rates evidenced among infantry units in the various theaters; the mean DNBI rate for support units in Okinawa was 0.93 per 1000 strength per day, while in Korea the support troop DNBI rate was 0.76.

CORRELATIONAL ANALYSES

The correlational relationships between DNBI rates and casualty rates were then analyzed for the various operations. There were no significant relationships between DNBI rate and WIA or KIA for support troops in any of the operations, nor among DNBI and casualties during the Falklands operation. However, significant relationships existed for combat troops in Okinawa, Korea, and Vietnam.

Table 1 shows the correlations between DNBI rates and the WIA and KIA incidence of infantry units in Okinawa. The correlations between daily DNBI incidence and the same day's WIA and KIA incidence were significant, as were the correlations between DNBI incidence and the casualty rates observed on the immediately preceding days. The correlation coefficients between DNBI and total casualty (WIA +

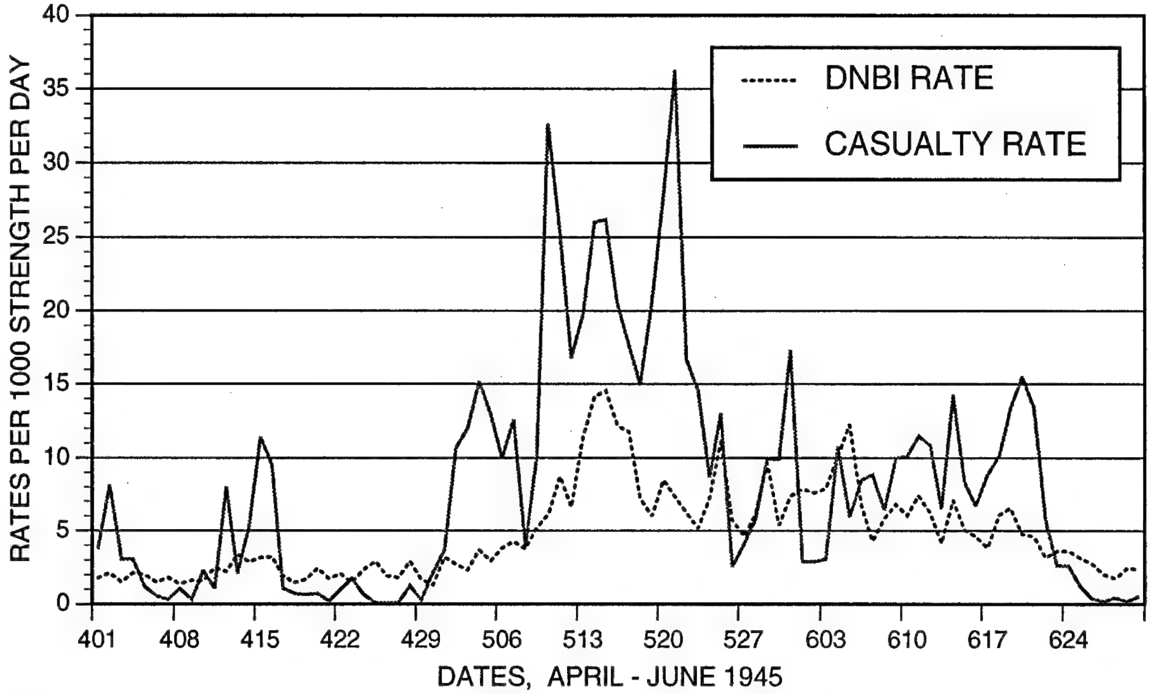

Figure 1. Presentation rates of disease and non-battle injury (DNBI) and casualties among infantry battalions during the Okinawa Operation (1945).

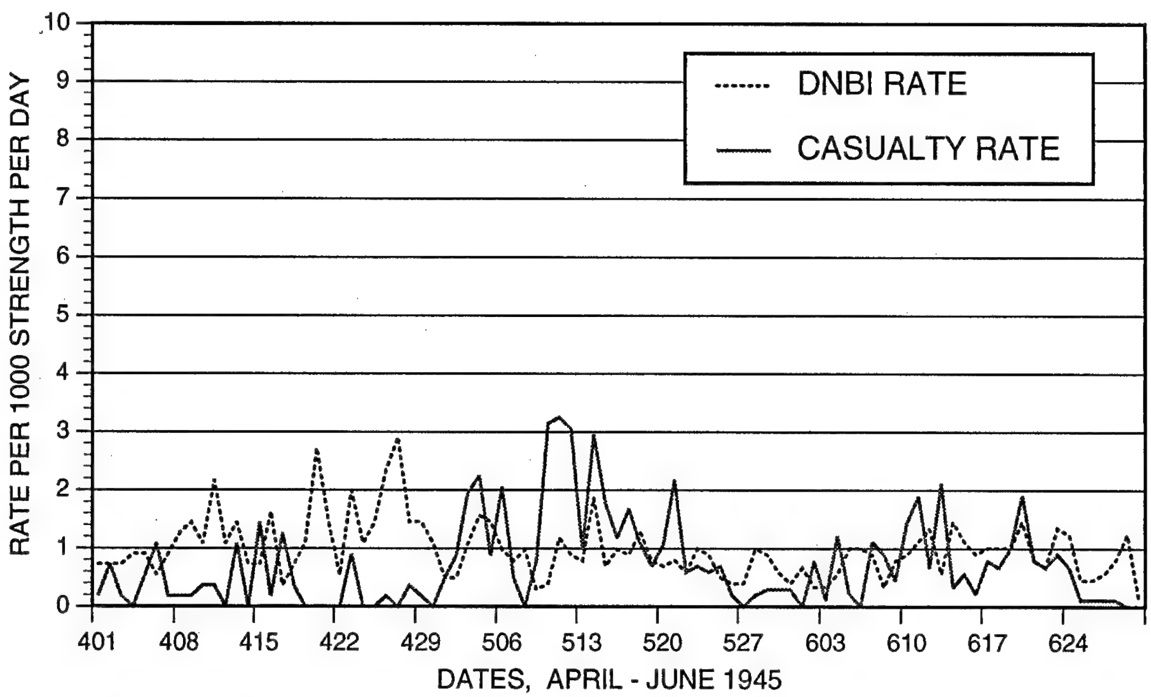

Figure 2. Presentation rates of disease and non-battle injury (DNBI) and casualties among combat support troops during the Okinawa Operation (1945).

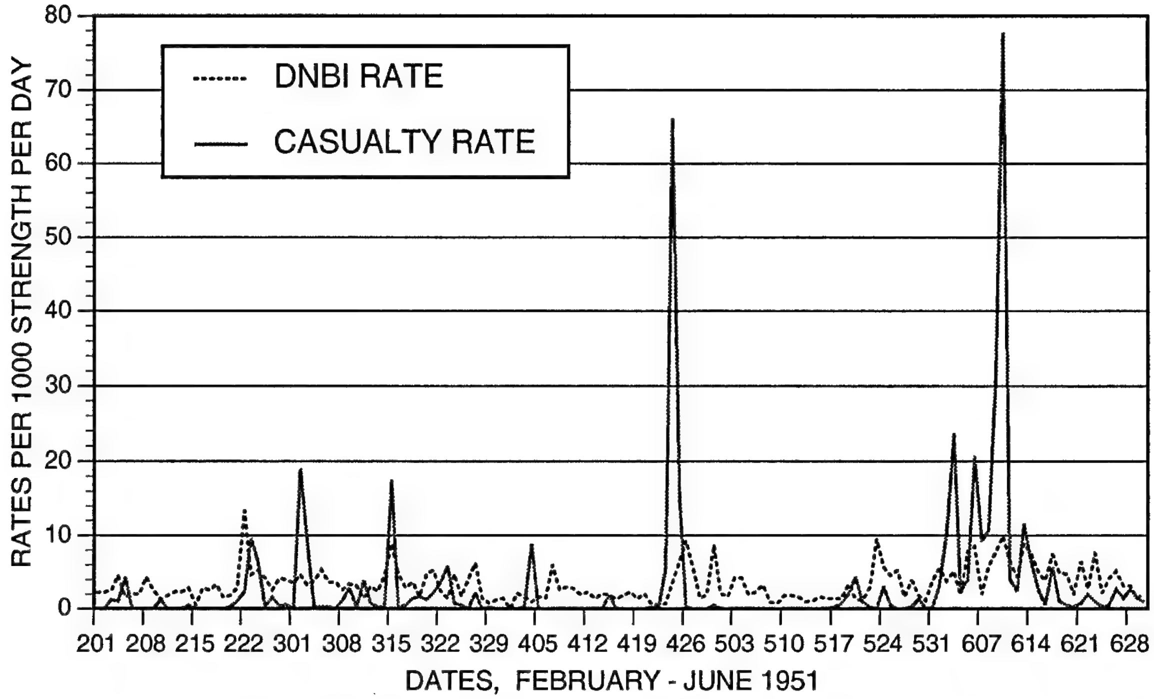

Figure 3. Presentation rates of disease and non-battle injury (DNBI) and casualties among infantry battalions during a five month period of the Korean Conflict (1951).

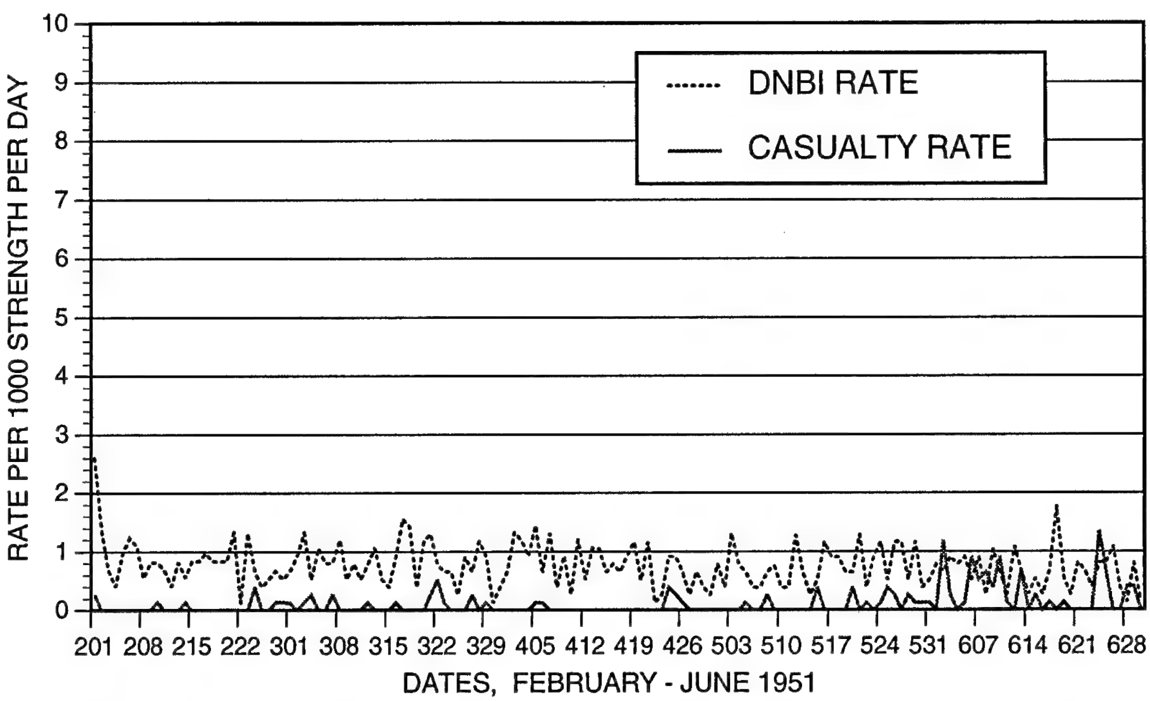

Figure 4. Presentation rates of disease and non-battle injury (DNBI) and casualties among combat support troops during a five month period of the Korean Conflict (1951).

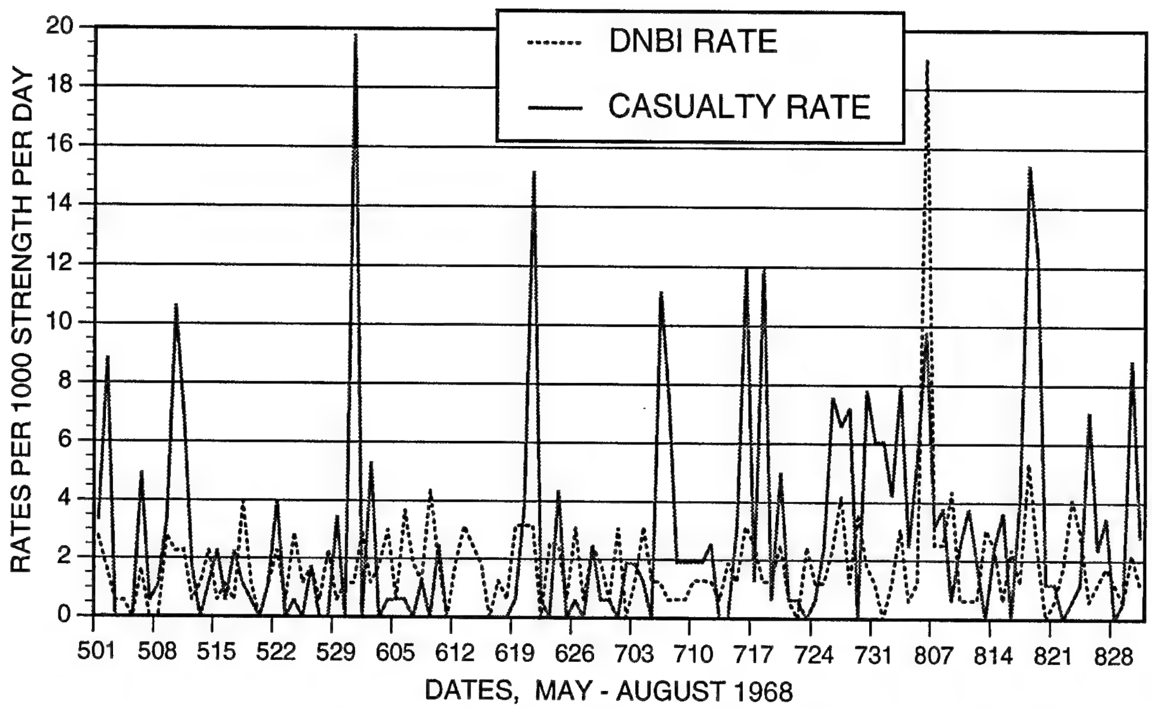

Figure 5. Presentation rates of disease and non-battle injury (DNBI) and casualties among infantry battalions during a four month period of the Vietnam War (1968).

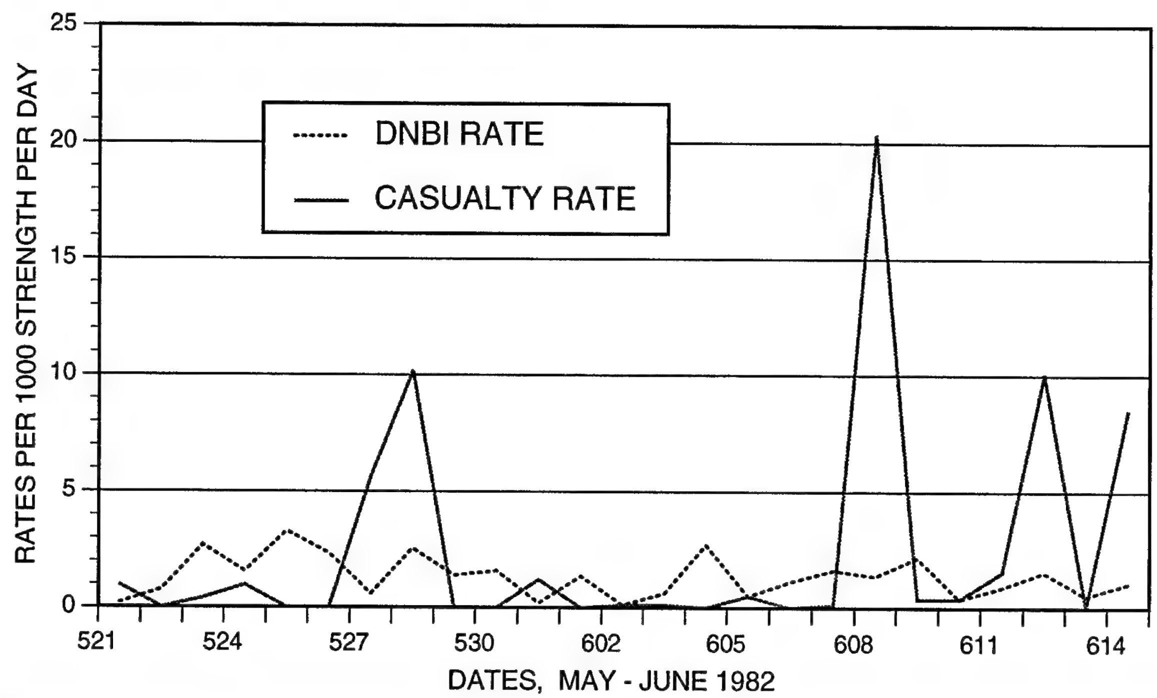

Figure 6. Presentation rates of disease and non-battle injury (DNBI) and casualties during the Falklands War (1982).

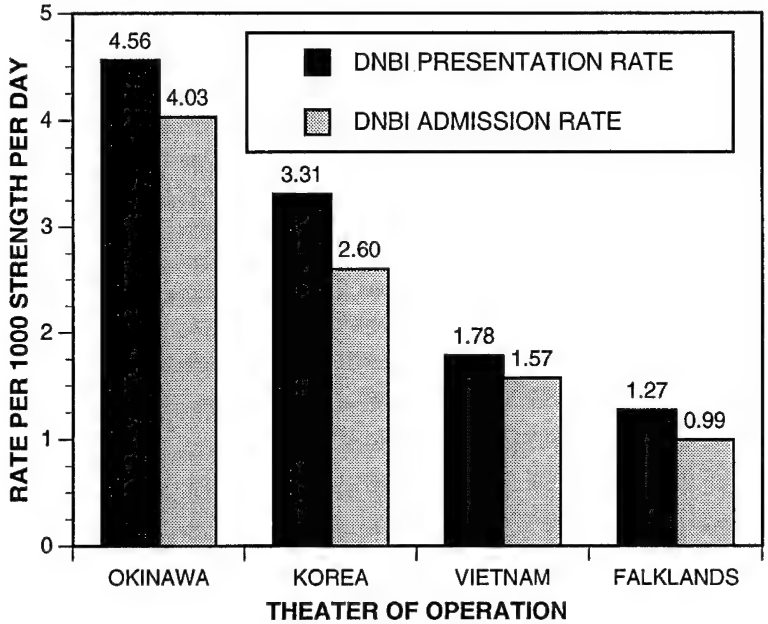

Figure 7. Rates of disease and non-battle injury (DNBI) among combat troops across theaters of operation.

Table 1. Correlations between DNBI rates and casualty (WIA, KIA) incidence; USMC infantry in Okinawa

r_{DW} = .675**	r_{DK} = .601**
$r_{D\text{-}1W}$ = .639**	$r_{D\text{-}1K}$ = .558**
$r_{D\text{-}2W}$ = .585**	$r_{D\text{-}2K}$ = .479**
$r_{D\text{-}3W}$ = .601**	$r_{D\text{-}3K}$ = .485**
$r_{D\text{-}4W}$ = .679**	$r_{D\text{-}4K}$ = .540**
$r_{D\text{-}5W}$ = .604**	$r_{D\text{-}5K}$ = .507**
$r_{D\text{-}6W}$ = .493**	$r_{D\text{-}6K}$ = .419**
$r_{D\text{-}7W}$ = .430**	$r_{D\text{-}7K}$ = .318**
$r_{D\text{-}1/7W}$ = .704**	$r_{D\text{-}1/7K}$ = .627**
$r_{D\text{-}8/14W}$ = .499**	$r_{D\text{-}8/14K}$ = .377**
$r_{D\text{-}15/21W}$ = .212	$r_{D\text{-}15/21K}$ = .222
$r_{D\text{-}21/28W}$ = .002	$r_{D\text{-}22/38K}$ = .038

** = $p < .005$.

r_{DW} = correlation between DNBI and WIA incidence.

$r_{D\text{-}1K}$ = correlation between DNBI and previous day's KIA incidence.

$r_{D\text{-}8/14W}$ = correlation between DNBI and 8–14 day's prior WIA incidence.

KIA) incidence were: same day (r_{DC}) = .674; DNBI with previous day's casualties ($r_{D\text{-}1C}$) = .636; DNBI with casualties incurred 2 days earlier ($r_{D\text{-}2C}$) = .577; $r_{D\text{-}3C}$ = .592; $r_{D\text{-}4C}$ = .667; $r_{D\text{-}5C}$ = .598; $r_{D\text{-}6C}$ = .490; and $r_{D\text{-}7C}$ = .418. Because the correlations between DNBI rates and the casualty incidence on each of the preceding seven days reached a high level of statistical significance ($p < .005$), correlational analyses were run between DNBI and the aggregated WIA and KIA rates of the preceding week, the aggregated casualty rates of two weeks earlier (8–14 days prior to DNBI incidence), three weeks earlier, and of four weeks earlier. Table 1 indicates that there are significant positive correlations between DNBI incidence and the casualties sustained up to two weeks prior.

Table 2 displays the correlation coefficients for the infantry troops serving in Korea. While significant correlations again were observed between daily DNBI incidence and the casualties incurred on the immediately preceding days, the coefficients were smaller than those of the troops deployed to Okinawa, and statistical significance was only evidenced for the single preceding week. Table 3 indicates two significant correlations between DNBI and the casualties incurred among the troops deployed to Vietnam. Only the correlation coefficients of DNBI and the concomitantly occurring WIA and KIA were significant.

Stepwise multiple regressions then were performed for the three data sets in which significant correlations existed between DNBI and casualty incidence to ascertain the existence of

Table 2. Correlations between DNBI rates and casualty (WIA, KIA) incidence; USMC infantry in Korea

r_{DW} = .366**	r_{DK} = .219*
$r_{D\text{-}1W}$ = .289**	$r_{D\text{-}1K}$ = .203
$r_{D\text{-}2W}$ = .290**	$r_{D\text{-}2K}$ = .274**
$r_{D\text{-}3W}$ = .345**	$r_{D\text{-}3K}$ = .314**
$r_{D\text{-}4W}$ = .223*	$r_{D\text{-}4K}$ = .147
$r_{D\text{-}5W}$ = .167	$r_{D\text{-}5K}$ = .070
$r_{D\text{-}6W}$ = .228*	$r_{D\text{-}6K}$ = .237**
$r_{D\text{-}7W}$ = .191	$r_{D\text{-}7K}$ = .067
$r_{D\text{-}1/7W}$ = .462**	$r_{D\text{-}1/7K}$ = .426**
$r_{D\text{-}8/14W}$ = .133	$r_{D\text{-}8/14K}$ = .077
$r_{D\text{-}15/21W}$ = −.121	$r_{D\text{-}15/21K}$ = −.159
$r_{D\text{-}21/28W}$ = −.211	$r_{D\text{-}22/38K}$ = −.190

* = $p < .01$.
** = $p < .005$./
r_{DW} = correlation between DNBI and WIA incidence.
$r_{D\text{-}1K}$ = correlation between DNBI and previous day's KIA incidence.
$r_{D\text{-}8/14W}$ = correlation between DNBI and 8–14 day's prior WIA incidence.

Table 3. Correlations between DNBI rates and casualty (WIA, KIA) incidence; USMC infantry in Vietnam

r_{DW} = .229*	r_{DK} = .210*
$r_{D\text{-}1W}$ = .023	$r_{D\text{-}1K}$ = .096
$r_{D\text{-}2W}$ = −.070	$r_{D\text{-}2K}$ = −.030
$r_{D\text{-}3W}$ = .103	$r_{D\text{-}3K}$ = .010
$r_{D\text{-}4W}$ = .068	$r_{D\text{-}4K}$ = −.016
$r_{D\text{-}5W}$ = .054	$r_{D\text{-}5K}$ = −.066
$r_{D\text{-}6W}$ = .021	$r_{D\text{-}6K}$ = .036
$r_{D\text{-}7W}$ = .111	$r_{D\text{-}7K}$ = .167
$r_{D\text{-}1/7W}$ = .107	$r_{D\text{-}1/7K}$ = .089
$r_{D\text{-}8/14W}$ = .096	$r_{D\text{-}8/14K}$ = .076
$r_{D\text{-}15/21W}$ = .074	$r_{D\text{-}15/21K}$ = .036
$r_{D\text{-}21/28W}$ = −.017	$r_{D\text{-}22/38K}$ = −.054

* = $p < .05$.
r_{DW} = correlation between DNBI and WIA incidence.
$r_{D\text{-}1K}$ = correlation between DNBI and previous day's KIA incidence.
$r_{D\text{-}8/14W}$ = correlation between DNBI and 8–14 day's prior WIA incidence.

any significant predictor variables. An r^2 of 0.585, meaning 58% of the variance in DNBI incidence was accounted for by the predictor variables, was obtained in the regression analysis performed on the Okinawa data; the r^2 for the Korea data was 0.329, while the r^2 for the Vietnam data was 0.047. For each operation there was at least one significant predictor variable in estimating DNBI incidence, and these variables corresponded to some of the larger correlation coefficients observed in the analyses of the daily incidence rates (see Table 4).

DISCUSSION

The graphical depictions of DNBI incidence indicated that these rates clearly do not occur in a vacuum. DNBI rates are higher among combat troops than support troops and the pulses in combat troop DNBI rates parallel and immediately follow pulses in casualty incidence. These relationships between DNBI and casualty incidence were further borne out by correlational analyses, particularly in the data of the Okinawa and Korea deployments. In general, there was a reduction in the magnitude of the correlation coefficients as a function of increasing spans of time between DNBI incidence and casualty incidence. This trend was observed with both the daily and weekly casualty rate analyses.

The regression analyses indicated that some of the variables yielding significant correlations could be used as predictors of DNBI incidence. It is important to note that very little variance was actually accounted for within the Vietnam DNBI rates (4.7%), and that progressively more was accounted for within the Korea rates (33.5%) and the Okinawa rates (58.5%). This trend toward less "accounted for" variance from Okinawa to Korea to Vietnam is likely related to a lessening of battle intensities over time. The Okinawa operation was a 91-day engagement in which there was a relatively high sustained tempo of fighting. The Korea and Vietnam conflicts were different in that, while the tempo of operations reached high levels from time to time, such a level was not generally sustained over several months as in Okinawa. Higher sustained battle tempos would be more likely than shorter less intense operations to yield higher rates of psychiatric casualties and increased illness incidence due to compromised immune systems; thus, the more prolonged heightened tempos would be reflected by both higher casualty rates and increased DNBI incidence. This notion is sup-

Table 4. Regression equations for predicting DNBI incidence of infantry during ground operations

OKINAWA

Variable	B	SE B	Beta	T	Sig T
PREV4WIA	0.214	0.039	0.458	5.41	.001
WIA	0.194	0.039	0.416	4.93	.001
(Constant)	2.091	0.356		5.87	.001

DNBI = 2.09 + (PREV4WIA*0.214) + (WIA*0.194)

KOREA

Variable	B	SE B	Beta	T	Sig T
WIA	0.150	0.034	0.574	4.37	.001
PREV3WIA	0.060	0.019	0.230	3.17	.002
PREV6KIA	0.647	0.215	0.211	3.00	.004
PREV2KIA	0.607	0.220	0.198	2.76	.006
KIA	−.897	0.400	−.293	−2.24	.026
(Constant)	2.692	0.188		14.33	.001

DNBI = 2.69 + (WIA*0.150) + (PREV3WIA*0.060) + (PREV6KIA*.647) + (PREV2KIA*.607) + (KIA*−.897)

VIETNAM

Variable	B	SE B	Beta	T	Sig T
WIA	0.130	0.054	0.218	2.39	.018
(Constant)	1.511	0.226		6.68	.001

DNBI = 1.51 + (WIA*.130)

ported by the lack of significant correlations between DNBI and casualty incidence in the very brief OPERATION CORPORATE.

But to return to the earlier discussion of the system, the loop, and the man — why should a combat unit not be viewed as a system? As with other systems, all parts need to work in unison if it is to effectively operate. The health of a military unit, thus, may be considered an OR factor. In this context, operations research has progressed from the loop, to the man-in-the-loop, to "men as the loop". If there are too many component failures within the loop, that is, if the DNBI incidence of the infantry unit is high, the effective functioning of the system is inhibited. System inhibition indeed begins to sound like an OR factor. But "soft OR"? If the soldiers are laying in bunks you can reach out and touch them or their diseased/injured body parts. Most soft OR factors are considerably less tangible.

Examination of the daily graphs, the correlations, and the regressions, gives rise to the question, "What is it that is being measured"? Simultaneous peaks of DNBI and casualty incidence were evidenced. But there were also pronounced pulses of DNBI incidence that occurred 3–4 days after casualty peaks. The stress of the combat situation appears to take a toll immediately, likely in the form of battle fatigue cases. However, this stress may also have a weakening effect on the immunological systems of soldiers, with a consequent rise in illness incidence after sufficient time for disease incubation.

In summary, the dynamics of DNBI incidence are best illustrated by Figure 8 in which there is a stressor (battlefield conditions) applied to a system (the military unit) which results in immediate and delayed component failures. The naturally occurring DNBI incidence within a unit perhaps should be regarded simply as an OR factor. But DNBI attrition related to the pulses in combat tempo is much harder to predict, and might more aptly be considered a soft factor. In either case, DNBI incidence represents system component failure and must be planned for and modeled accordingly.

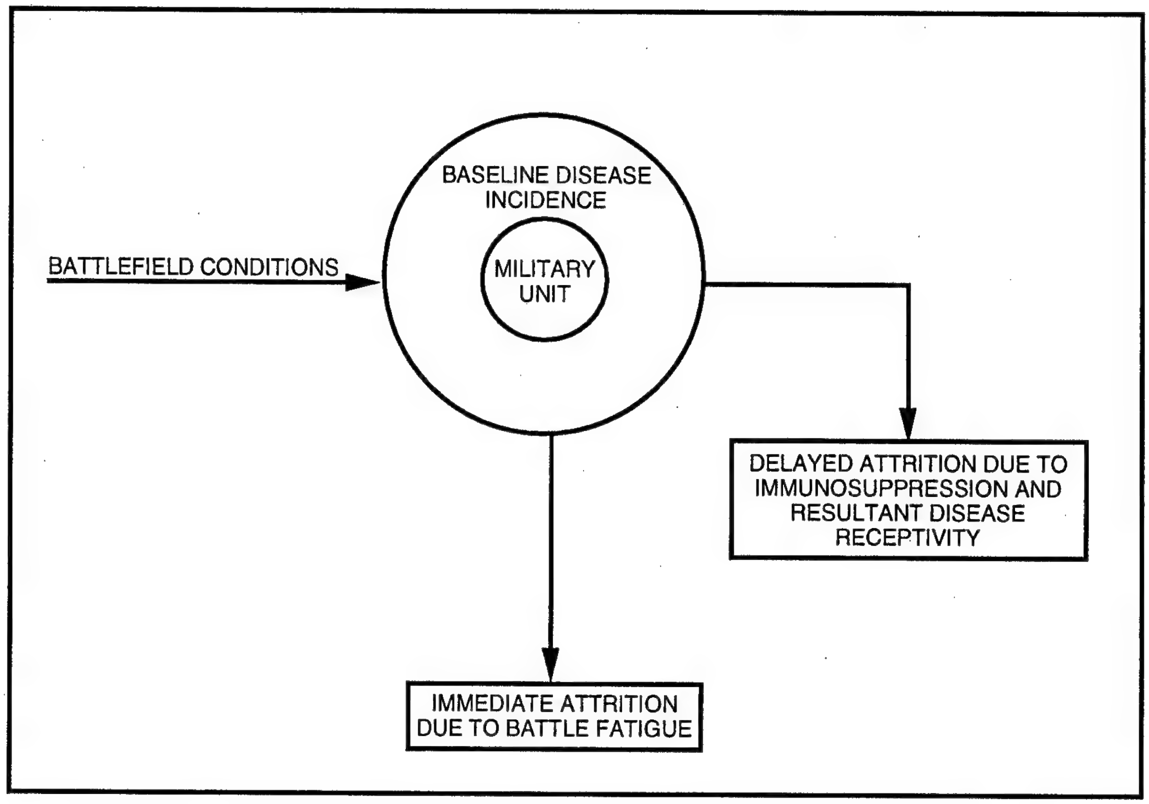

Figure 8. Dynamics of unit attrition resulting from disease and nonbattle injury incidence.

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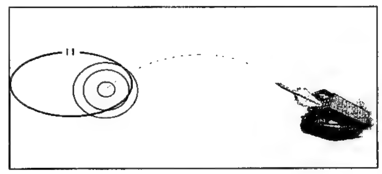
Volume II
Area 1

Conventional Weapons Effects (Ground)



Samuel H. Parry, Editor

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May 1995

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Realtime learning of doctrine and tactics using neural networks and combat simulations

Dr. John D. Morrison

Los Alamos National Laboratory

ABSTRACT

Limitations of the traditional Artificial Intelligence paradigm restrict its capacity to support manageable and verifiable knowledge base development for expert system simulations. This report argues that because expertise acquired in dynamic military domains is associated with unique aspects of memory and action-response sequences that are resistant to word-based cues and expression, an alternative model is required for acquiring and representing knowledge in these competitive environments.

Motivated by an emerging research into adaptive and neural models, this report documents a USA TRADOC supported research program that proposed and evaluated an adaptive model within the Army's high-resolution combat simulation—CASTFOREM. The prototype was designed to support a synthetic model of intelligence that represents complex goal functions, rule-based (deductive) reasoning in the presence of environmental activity that is consistent with expectation, as well as goal-based (inductive) reasoning in the presence of uncertainty—unfamiliar patterns of activity.

The experiment demonstrated that the prototype is not only capable of generating effective tactics, but the prototype converges to stable, rule-based behavior quickly and efficiently. These results motivate further research into the application of intelligent simulations to broader, long-term goals such as developing and optimizing tactics for developmental hardware and software systems.

MOTIVATION

Under the Army Model Improvement Program that began in the mid 1970s, the current family of Army combat simulations was developed with the capacity to represent tactical decision making. The knowledge-based approach, the predominant artificial intelligence paradigm at the time, was chosen as the vehicle for representing approved doctrine. Model developers felt that this approach would reduce stochastic variance, enhance user confidence in the analytical product, and reduce scenario development time.

However, the knowledge-based approach has shown some limitations not fully appreciated within the artificial intelligence (AI) community when the technology initially emerged (Boden, 1984; Partridge, 1987; Waltz, 1983). These shortcomings are manifested by difficulty in developing, maintaining, and validating knowledge bases. In addition, symbolic approaches to machine learning have been less than effective in unstructured, continuous domains (Carbonell, 1989). As a result, current knowledge-based computer simulations have only limited capacity to identify the influence of the existing knowledge bases or for understanding how alternative behaviors (tactics) might improve system performance. This last limitation is especially significant in the development and testing of automated decision logics to support future robotic vehicles and decision aids that will operate in concert with humans.

Recently, research efforts have demonstrated success with connectionist networks, for representing knowledge. Network architectures may overcome some of the limitations associated with current production systems and may facilitate learning. The objective of the research reported here was to evaluate the potential for improving Army combat models by replacing a portion of the current symbolic, rule-based system with a neural network model that represents complex goal functions and simultaneously supports effective rule-based (deductive) reasoning in the presence of environmental activity that is consistent with expectation, as well as adaptive, goal-based (inductive) reasoning in the presence of unfamiliar patterns of activity.

An Expert System Simulation

All expert system models share a common structural representation of human memory. In practical terms, they tend to be domain-specific models of memory because they are confined to a specific body of knowledge and a selected set of classification strategies. All expert systems have three common elements: a set of facts, a set of rules of inference, and a program that manipulates the symbols and interprets the results.

The Department of Defense has been a leader in the use of expert system technology. One major application is the representation of accepted doctrine in combat simulations. This research focuses on the expert system component of the Army's Combined Arms and Support Task Force

Evaluation Model (CASTFOREM), a large, stochastic model of ground and air combat that uses an expert system to schedule human activities as events as shown in Figure 1. Currently, this model does not have the capacity to assess, learn or create new knowledge.

Expert System Limitations

Expert systems were received with great enthusiasm in the late 70s and early 80s as the first practical fruits of years of AI research. In the last few years, however, it has become obvious to many that these original systems, like any first-generation technology, have design deficiencies that limit their long-term utility. Experienced users of expert systems encounter consistent difficulty with the development of knowledge bases. Because expert systems are typically applied to relatively complex decision environments, the so-called "knowledge engineering bottleneck" is in expressing complex sets of rules in a cogent and coherent form while maintaining some control on the growth of the program.

The difficulty of maintaining a coherent and transparent knowledge base increases as different experts, knowledge engineers, and data base managers modify it. Because production rules exist as relatively independent condition-response pairings, the tendency is to develop the rule base as an extended set of independent situational analyses. While each rule may be appropriate to that circumstance, there is no basis for discerning, from the resulting product, any underlying cognitive structure or recognizing inconsistencies or holes in the rule base. Over time, the rule base has a tendency to expand, yet such expansion is difficult to manage. The net effect on simulations can be the introduction of a poorly understood, yet powerful, source of variability. The impact on the knowledge base is unknown to the analysts, and it would be unrealistic to assume that it is uniform over all scenarios.

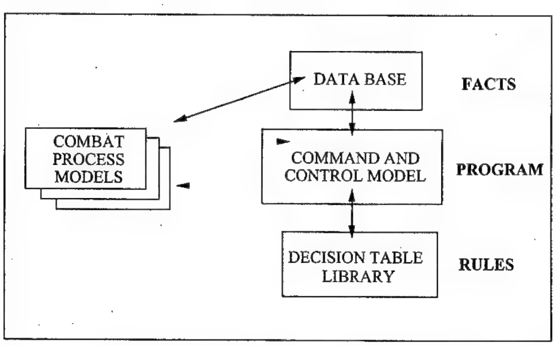

Figure 1. CASTFOREM Command and Control

Expert systems are also inherently redundant. Because each rule is essentially independent, each conditional fact in the "if" portion of the production, and each order in the "then" portion must be explicitly stated. In expert systems that use frame or decision table structures, redundancy is further compounded because each table or frame requires a complete and independent set of rules. In CASTFOREM, the rule base can grow from a basic set of about 1000 rules and 2000 orders to a structure of 2500 Decision Tables encompassing 21,000 Rules, 9000 Condition Statements, and 16,000 Order Statements.

The current approach to developing knowledge bases may make the rule base unverifiable. While it is usually assumed that the person generating the rules has demonstrated some expertise in the field, there is little or no basis for determining that the resulting rules represent any level of optimality or consensus of expert judgment. The net result is a system in which the embedded doctrine and tactics may be nothing more than one person's opinion.

In summary, knowledge base development is a manpower-intensive activity whose product may be unsuitable for verification. At best, the rule base represents a collection of relatively independent cognitive theories. The net effect is a reduced capability to use knowledge-based simulations in analyzing behavioral issues for complex man-machine systems. An additional limitation of current expert systems is their inability to respond to changes in dynamic environments.

The basic assumption of early knowledge-based research efforts was that a tractable number of general problem-solving heuristics would satisfy the information processing requirements of intelligent machines. Practical applications have been resistant to this assumption. There is now considerable demand for "second generation expert systems" with a capacity for self-adaptivity (Partridge, 1987). Such a capability should allow the machines themselves, based on an underlying set of performance goals, to identify the rules that contribute to optimal performance and make the required changes. Additionally, simulations are

uniquely capable of providing realistic "world models" of future combat. Adaptive simulations could, therefore, serve as powerful adjuncts to field training for developing improved tactics for future battlefield environments.

Potential Applications and Enhancements

Typically, simulation-based analyses have focused on how system characteristics and organizations influence force performance. Although human judgment (tactics and doctrine) strongly influences force performance as well, it has remained inaccessible to rigorous analysis. This limitation is becoming unacceptable for three reasons.

One, the "come as you are" nature of modern warfare makes it important that forces deploy into combat with fully matured tactics and doctrine.

Two, robots and automated decision aids have assumed an important role in defense and commercial systems. While these systems are extremely complex, they preserve knowledge manually extracted from human experts. Not only is it difficult to determine if this knowledge applies to future conditions, it is difficult to determine the adequacy of the automated system in a realistic competitive environment. While humans adapt reasonably well to unexpected situations, machines, even those with embedded knowledge, do not. Consequently, the failure to develop, test, and maintain knowledge bases for automated systems within realistic current and future environments contributes to the vulnerability of these systems. Simulations provide a powerful tool for developing and validating the specifications and rule bases for such automated systems.

Three, emerging AI technology may now support learning within knowledge-based simulations. However, the modeling community has yet to exploit simulations unique promise for experimenting with alternative strategies, human factors, and levels of training. Maintenance problems with the existing expert system and the requirement to develop optimum tectics and doctrine creates the need for new knowledge-based systems that are more adaptable.

BACKGROUND

Over the past 25 years, artificial intelligence research has focused on well-ordered and well-behaved problem domains. However, learning necessitates understanding the relationship between the current environment and previously accumulated knowledge of the world—the ability to discriminate and adapt to change in competitive worlds. Practical learning involves collecting and storing environmental information so that the intelligent agent can effectively support, through reasoning skills, subsequent interaction with that environment. At present, two paradigms dominate the AI literature. The first, the symbolic school, incorporates research conducted under the Physical Symbol System Hypothesis (PSSH; Newell, 1980). The second major paradigm uses parallel distributed networks to organize and apply acquired knowledge. A field associated with this second paradigm, adaptive systems theory, incorporates learning effective response strategies in physical environments.

To a large degree, the symbolic paradigm derives its legitimacy from an association with fundamental theories that matured during the same time period in the fields of cognitive psychology, linguistics, and computer science. The research conducted under these interrelated fields has contributed to the development of a relatively common set of theories that support the notion that reasoning is a procedure by which a finite set of *discrete* symbols and a tractable set of rules can be manipulated to represent the essential aspects of human intelligence. Implicit in this traditional view (Newell) is the notion that the word-based portion of memory serves as the basis for high level reasoning, specifically mental classification and planning.

This paper takes a view that is more closely aligned with adaptive systems theory. We claim that in non-lexical problem solving domains, the patterns applied by experts to classify their environmental stimuli and the mental models from which they generate responses, incorporate spatio-temporal patterns that cannot be implemented under the current symbolic paradigm.

Spatio-temporal images confound the logics that have been developed to support symbolic reasoning in a number of ways. First, spatio-temporal images are continuous rather than discrete. While the AI community has attempted to treat this phenomenon (Hayes,

1979), the treatments have been disappointing. The fundamental problem may be that discrete functions can *approximate* continuous real-valued functions, but they cannot *represent* them. Consequently, increased precision is purchased with increased complexity and since the demand for precision is unbounded, so is the complexity.

Second, spatio-temporal relationships that exist in the episodic memory of specific experiences, are probably not word based, or lexical, and are, therefore, resistant to recall by standard verbal interview techniques.

Third, expertise that is generated in spatio-temporal worlds may be more closely associated with procedural memory and not suitable for direct expression. We refer to such implicit knowledge as "inaccessible rules."

Fourth, while symbol-based models have been increasingly applied to representing causal relationships, they have been resistant to attempts to actually learn these relationships in unstructured, continuous environments (Michalski, Carbonell, & Mitchell, 1986) and, therefore, acquire knowledge within an automated representation—a simulation.

In summary, while word knowledge is generally normalized to common aspects of our experiences, other aspects of knowledge and memory are associated with unique sensory experiences and action-response sequences. To the extent that these experiences are related to environmental patterns that are not amenable to verbal expression or recall, they are beyond the scope of current symbolic theory and, consequently, current expert systems and knowledge engineering techniques. Because much of the knowledge that is associated with combat activities is acquired and applied in complex spatio-temporal environments, traditional symbolic models and methods are particularly difficult to apply to representing tactical knowledge.

Inaccessible Rules

Complex tactical environments generate complex behaviors. Often, the stimuli that prompt these behaviors are not even discernible to the practitioners—they have "learned" to associate them with effective behavior in a particular problem space. Rumelhart and McClelland (1986) refer to this phenomenon as the *inaccessible rule view* in that some human behavior, although rule based, is inaccessible to direct observation or verbal expression. This inaccessibility has hindered the utility of rule-based systems because, and this is tricky, much of what we know, we don't know; or what we know either cannot be, or has not been, extracted from the inaccessible rule form and recoded in lexical format. Part of this problem is derived from the natural limitation of languages and part is associated with our inability to extract hidden, non-lexical, knowledge.

McClelland and Rumelhart are not alone in identifying the existence of non-formalized rules of effective behavior, sometimes referred to as non-declarative or implicit knowledge. Studies have shown that experienced physicists and chess masters apply efficient forms of spatio-temporal templating to generate effective behavior (Chase & Simon, 1973; Chi, Feltovich, & Glaser, 1981). Because these results indicate the existence of classification strategies that are consistent, effective, but otherwise unexpressed, they support the claim that people apply mental models with non-lexical attributes to prototypical problems in a wide variety of domains. They further support the notion that, as a characteristic of human memory, the brain may be responsive to spatio-temporal patterns in natural environments but may also be incapable of internally recreating the signals that generate that behavior. Likewise, when the behavior is also non-lexical, it may be difficult for the expert to accurately express it verbally.

These observations imply that much of the expertise gained in operational environments is stored in that portion of memory that is not word-based. Therefore, this expertise is not only resistant to recall through traditional interview techniques, it also cannot be adequately expressed in current expert system programs. Neural network learning models, operating within a synthetic combat environment (CASTFOREM), may provide an opportunity to generate, refine, or verify tactics and doctrine in a synthetic environment. Understanding that specialists may distinguish between neural, artificial neural, distributed, and connectionist networks, this paper uses these terms as equivalent descriptions of a common paradigm.

Learning Models

During the 1960s, while AI continued to apply discrete representations of high-level de-

cision processes, control theory continued to apply continuous functions to representing low-level sensory activities related to engineering systems. Neural networks have emerged from cybernetics and control theory research as a powerful, but opaque, architecture for representing both levels of knowledge. These networks are particularly amenable to being trained to classify patterns (rules) in the presence of noise while reducing the redundancy and inherent complexities of symbolic, knowledge-based systems.

However, once trained, current neural models are, like expert systems, simple classification devices in that they respond to a single input data set without regard to preceding classification activities. Because of this both approaches are regarded as "one shot" classification devices. Control theorists refer to models of this class as Open Loop Controllers. In AI jargon, these models are referred to as "trainable pattern classifiers," and the adaptive process is referred to as "supervised learning."

As the name "neural net" implies, researchers remain motivated by a desire to use them to link the physiological and psychological aspects of cognition. In this regard, symbolic and distributed models draw credibility from their association with classical conditioning (Pavlov's experiment) in behavioral psychology (Rescorla & Wagner, 1972; Barto, 1985). Figure 2 shows the relationship between classical conditioning, network models that adapt in response to a reinforcing signal, and open-loop controllers.

Closed Loop or unsupervised learning models differ from open loop, trainable pattern classifiers in that they adapt their memory directly and continuously according to the response that their behavior elicits from the environment. Figure 3 reflects the general architecture for this more complex learning paradigm. Closed loop models support causal reasoning in that the model acquires, preserves, and applies cause and effect relationships through direct interaction with its environment.

Because they are directly responsive to a rational environment, closed-loop controllers evaluate their output indirectly—through their influence on the environment. Explicit goals provide the medium for evaluating the relationship between a *pattern* of behavior and a *pattern* of environmental response. To the extent that the response is favorable with respect

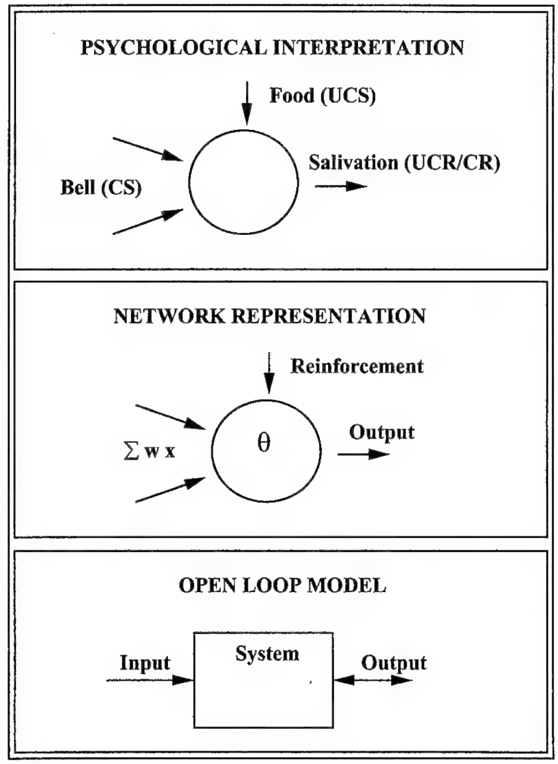

Figure 2. Pattern Classification Models

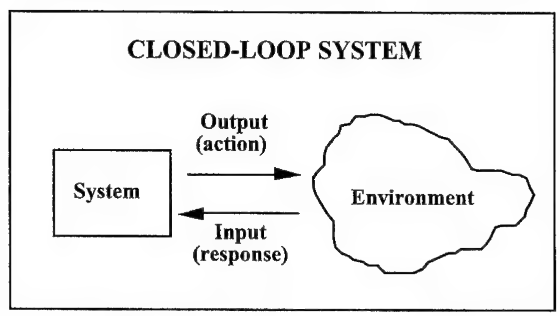

Figure 3. Closed Loop Systems

to the currently active goal, recent behavior is reinforced. To the extent that the response is unfavorable, further behavior of that type is inhibited. Because models of this class do not require an external evaluation mechanism, they are referred to as "unsupervised" learning models. The learning model developed for CASTFOREM was of this class.

To date, automated learning has typically involved attempts to infer or deduce structure from knowledge in temporally static domains. In this regard, single-function pattern classifi-

cation typically differs from practical learning in that the program attempts to discern the characteristics of a narrowly-defined problem that is, if not independent of other activity in the domain, at least relatively removed from it.

Unlike open-loop classifier systems, closed-loop or causal reasoning systems discern the relationships that exist between the environmental response associated with a particular behavior and the relationship of that response to a system-level goal. While the distinction is generally one of degree, classifiers discern the nature of a system only with respect to a single performance measure, while practical learning is oriented toward behavior of a system with respect to the non-uniform physics of a particular environment. This research effort used an open-looped architecture to learn rule-based behavior then modified it to a closed loop architecture in order to allow the model to learn.

"NEURAL" NETWORK SIMULATION

"Neural" architectures are based on a common computing or Threshold Logic Units (TLU), Figure 4, with nodes associated with concepts and arc weights representing similarity. The implementing element consists of a concept node, all of the input signals, and an output signal. TLU compute the function $\mathbf{W} \cdot \mathbf{X} - [\boldsymbol{\theta}]$ for a series of inputs ($\mathbf{X}$) and a unit threshold characteristic ($[\theta]$).

Because these units implement linear surfaces within some multidimensional measurement space, they can be connected to form multiple surfaces that partition the space into different decision regions (Nilsson, 1965). Training, or modification of the decision surfaces so that they maintain consistency with some known phenomenon, is realized by adjusting the weights and thresholds to ensure that the appropriate unit activates for representative samples of a given population. In the discrete representations of Long Term Memory (LTM) cited above, $x_i(t)$ is interpreted as the instantaneous output energy of an activated or "fired" input unit at time (t).

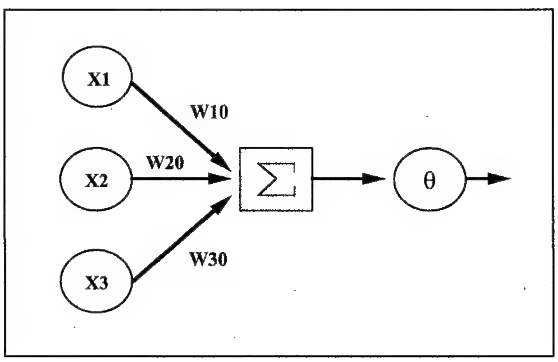

Figure 4. Threshold Logic Unit

Models that treat Short Term Memory (STM) incorporate the effects of gradual decay in the output signal. Between activations, the activation energy dissipates at a rate consistent with the previous firing history of the unit. Because STM is the residual energy from a previous activation, it can also be associated with attentional phenomena and is referred to here as the attentional trace because it serves to proportionally localize currently active goals and activities. This trace is important to maintaining consistent and coherent behavior patterns and in effectively focusing reinforcement. *One of the unique features of the model presented here, is that the physical processes associated with STM are represented explicitly for each unit.*

Connectionist Simulations

Within a knowledge-based simulation, a connectionist model may provide a number of advantages over traditional production system approaches. Many of these advantages relate to the inherent parsimony and coherence associated with network systems in general. While parsimony and coherence can contribute to clarity, this characteristic is not necessarily a by-product of networks. A considerable advantage of this approach is that network systems readily support automated learning. However, the linkage between learning, parsimony and coherence is the development of a structure for characterizing an active goal-hierarchy that represents a logical and coherent cognitive theory within some world model. The general, open-loop, neural architecture as shown in Figure 5, consists of three unit types:

- input (perception) units;
- internal (conceptual) units; and
- output (action) units.

Input units are facts or state conditions. Within the context of the simulation, inputs consist of facts contained in the data base or derived from previous events. Within the context of a production (expert) system, these units are associ-

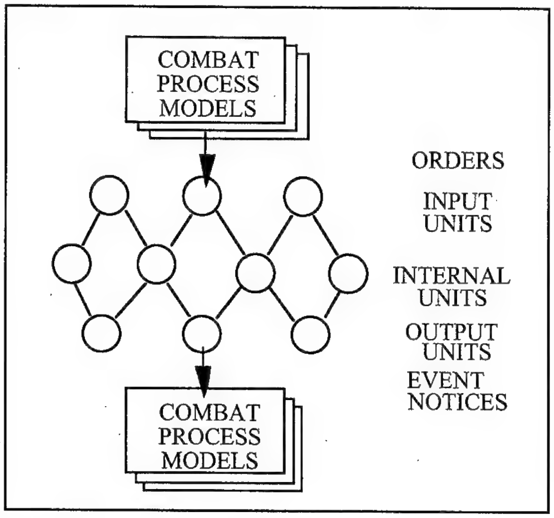

Figure 5. A Connectionist Simulation Environment

ated with the query or "if" component of the if-then production. Within the context of the physiology of cognition, input constitutes a stimulation. As another perspective, consider these elements as the input assumptions that make a given goal viable.

Internal units are located between the input units and the output units. Within the context of the simulation they link the if-then-else pairings appropriate to a set of facts. Within the context of a production system, the pattern of connectivity between these units is the knowledge component of the knowledge base.

Output units are events to be scheduled. As such, output units are goal-action primitives, such as "stop." These are the "then" component of the if-then productions. Within the simulation, output units are implementation messages to be passed to the physical process models.

Within the context of a simulation, events have two aspects. The first aspect, related to activities that precede the completion of the action, constitutes an intention or goal. Specifically, it constitutes the desire to change the environment. The intention has its full meaning embedded in the initial environmental state that prompted the selection of the goal. The second aspect is the effect of the event, or behavior, on the environment. Behavior is then expressed as a logical and continuous pattern of stimulus-response, wherein a cognitive element possesses some internal goal structure which controls its response to environmental stimuli.

While the preliminary research into the application of connectionist architectures to stand-alone expert systems is emerging (Gallant, 1988; Lirov, Rodin, McElhaney, & Wilbur, 1988), there are some fundamental differences between these applications and expert system simulations. First, most rule-based systems are temporally static in that time exerts no influence on the validity and applicability of the rules. Second, most connectionist models are supervised learning models that learn with a teacher. Although connectionist learning systems, expert system simulations, and most recently, connectionist expert systems have been successfully demonstrated, the development of an expert, rule-based learning system within a simulation remains elusive.

Adaptive Simulations

The knowledge-based simulation environment shown in the preceding Figure 5 is an expression of some control law or cognitive theory. To the extent that the implicit rule-base is derived from a set of underlying assumptions about the environment and performance expectations, it is a belief system. However, in the existing form, the goals are not expressed and the underlying assumptions are not evident. Consequently, they are opaque to the analyst and cannot be directly applied to the learning process.

Understanding that goals and rules are either explicitly or implicitly associated with all intelligent systems, we distinguish goal-based systems as those in which the behavioral (versus computational) goals are explicitly represented and suitable for adaptation. When expressed in hierarchical form as shown in Figure 6, the relationships that exist between goals and subgoals provide a basis for relating overall goal-based system performance to specific assumptions about the viability and contribution of the supporting subgoals. In this form, the belief system is a full expression of some control theory in that the system's relationship with the environment, as expressed in a set of feasible state conditions, can be related either to overall system performance measures or to the

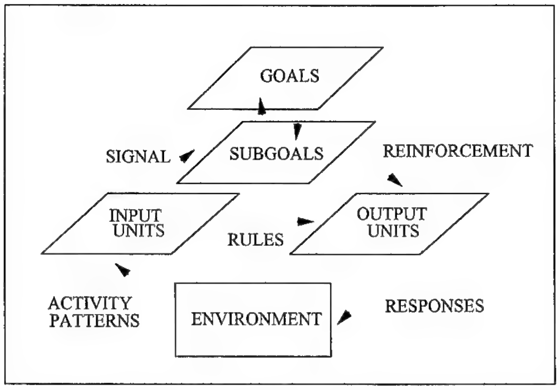

Figure 6. A Goal-Based, Closed-Loop Learning Model

relationships and the subgoals that support them.

Simulations provide a more difficult, albeit realistic, learning environment than the static, associative problems to which learning models have been, typically, applied. Within the simulation, as in real life, the learning mechanism must determine from a pattern of recent history the extent to which previous events in that history led to a state inconsistent with expectations. In such a real world environment, the unique characteristic of reinforcement learning is in assessing the influence of time on the existing inconsistency. In short, because feedback is not always instantaneous, there is no guarantee that the cause of the anomaly was the most recent event. In order to develop such a reinforcement learning model, two credit assignment problems must be resolved:

- how to focus reinforcement/change on the principal contributors (structural credit assignment); and
- how to apportion reinforcement according to recency (temporal credit assignment).

Goal-Based Reasoning

New research into the development of qualitative or goal-based reasoning models is motivated by the desire to overcome the previously discussed limitations based on an understanding of the causal relationships peculiar to that domain (Bobrow, 1985). Because these relationships are relatively well known for physical processes, current models emphasize these stable causal behaviors. However, current qualitative models appear resistant to *discovering* causal relationships for the apparently inconsistent human behaviors characteristic of competitive environments or problem spaces that involve multiple, competing goals.

These limitations of the current family of symbolic learning models support the view that an alternative approach may provide a more complete theory of memory. Although previous models suffered from the limitations of the early neural paradigms, new connectionist mechanisms motivate their reconsideration as reinforcement models that support learning in multiple, simultaneous modalities. Within the context of adaptive system theory, a small body of research into the use of closed-loop, connectionist, reinforcement learning models has demonstrated the power of this formalism in learning both symbolic and spatio-temporal relationships (Sutton & Barto, 1981; Anderson, 1987). To date, however, demonstrations of these models have been limited to problems involving only one system goal, using a dedicated reinforcement channel. In addition, they have not yet been demonstrated in problems of high dimensionality.

The goal of this research is to demonstrate an autonomous memory unit as the basis for a robust reinforcement model that learns spatio-temporal relationships (tactics) in a military environment. This learning model generates effective procedural, or rule-based, behavior from a goal-based architecture which further supports the development of secondary goals, as mental models, that are derived from experiences in a realistic combat simulation.

THE PROPOSED MODEL

Model Characteristics

Connectionist implementations are, typically, single-function, associative learning models constructed and implemented to apply a functional critic with single performance criteria. While unit-level blame is shared in these models proportional to participation, credit assignment is captured for the system as a whole. By employing a functionally specialized architecture, these restricted memory models also limit the autonomy of their computing units. It seems implausible that a system that displays the flexibility of the human mind can be constrained to the *a-priori* architectures associated with existing constructs. Because of these cen-

trally controlled critic(s), neither approach can be extended to a general model of intelligence. *In short, centrally crafted architectures are not naturally extensible.*

In order to overcome the limitations of the current family of expert system simulations through a goal-based, connectionist learning architecture, it is necessary to develop a general model of intelligence that is extensible to an expanding model of more complex environments. To be useful, this model supports the natural evolution or discovery of effective rule-based behavior within a goal-based reasoning system. The architecture is, therefore, extensible to greater resolution and broader range in the input and output pattern sets. The computing units are also sufficiently autonomous and flexible to preserve their effectiveness in varied and continuously changing environments. In order to achieve this extensibility, the basic computing units possess three characteristics: autonomy; stability; and plasticity.

The units are *autonomous* in that they possess all of the system features: memory; performance function; critic; and adaptive mechanism. The performance of the units are *stable* with respect to currently active system goals. While the goal of each unit is to be active, and it improves its relationship with its neighbors to that end, the firing rate is also influenced by the satisfaction of higher level goals. The units are also sufficiently flexible, or *plastic*, to avoid unbounded weight growth in the presence of anticipated activity. To that end, the units are capable of consistent rule-based behavior without adaptation. At the same time, based on goal-based reinforcement, units retain the capacity to modify that behavior when signal patterns indicate such adaptation will increase firing frequency.

Procedural Components of the Model

The process by which an environmental image generates a system response and adaptation is a two-stage procedure. First, the image propagates through the existing network to generate a system response. Second, and concurrent with system-level propagation, each unit conducts local adaptation by relating the most recent activity levels to their expectations. By allowing unit-level adaptation to proceed in parallel with system-level propagation, the system learns in "real time."

Propagation

Network propagation occurs with or without system-level reinforcement. When environmental activity is consistent with expectation, neither reinforcement nor inhibition is generated. This reflects a strictly rule-based, or deductive, response. In this case, the environmental image is propagated through the network using the traditional unit output function for TLU with one exception. When $\Sigma \mathbf{w} \cdot \mathbf{x} < [\theta]$, a "residual" activity level is computed as the unit's output. By incorporating the residual activation energy associated with short Term Memory (STM), the model preserves the dynamic aspects of the unit's history.

The effects of the environmental image, influenced by the bottom-up architecture, reach the higher level evaluation units which assess the impact of the current situation on the system's goals. If this influence is positive, a proportional reinforcing signal is generated causing the subordinate goal units to fire. Likewise, if the influence is negative, inhibition is generated. The essential characteristic of the procedure, is that during the course of the feedforward process, subgoals transmit output energy to their constituents proportional to the goodness of the current environment. *What distinguishes this model from previous reinforcement methods is that this transmission is indistinguishable to the autonomous unit from other signals.*

Adaptation

The procedures that have been developed to implement adaptation were derived from two principal assumptions. The first is that the system design should maximize higher level activation functions. This is achieved by organizing the system to provide bottom-up environmental images as well as top-down system-level reinforcement when the image pattern is inconsistent with expectation and goal maximization. The concept is consistent with the relationship between deductive reasoning, involving insignificant levels of top-down activity, and inductive reasoning which involves significant top-down activity. The second assumption, is that individual units want to fire. This

local goal causes units to, not only focus credit assignment on link activity that is highly correlated with firing, but also to adapt in the event of unexpected activity.

Related to these principal assumptions are two additional concepts. The first is that units want to operate efficiently. In this regard, adaptation reduces weight on those links whose activity is not well correlated with firing, and threshold values are set consistent with system noise. The second related concept is that units are creatures of habit. In this regard, the magnitude of any adaptation is proportional to the temporal distance between the current time and when firing is, or was, expected.

Long Term Memory—Structural Credit Assignment. The Long Term Memory trace or *eligibility pathway* reflects the extent to which the input activity on that pathway has been paired in the past with the element's output. By restricting, through inhibition, those activities that have been associated with a degradation of the system goal, these pathways ultimately reflect the extent to which the input activity has been correlated to effective unit output. Therefore, when pattern **x** has been consistently associated with reinforcement that has generated a firing of y, then **x** should fire y by itself. At some point, the relative contribution of that behavior to the objective function and environmental condition stabilizes and the reinforcement signal reduces to 0. However, by this time the stimulus-response (cause and effect) relationship is stronger and less reinforcement is necessary. In this way, the rule-based activity "weens" itself from reinforcement.

In order to realize this effect, the weights of the constituents are modified in proportion to their deviation from expected behavior. When the local unit and its constituent are behaving consistent with expectation, no local reinforcement is required. However, when the activity of one is inconsistent with the history it shares with the other, adaptation is directed. Consistent with this relationship:

- when units are relatively active, make modest weight adjustments;
- when units are relatively inactive, make substantial weight adjustments; and
- make corrections in proportion to current value.

Adaptation is physically realized by modifying autonomous unit characteristics in accordance with the appropriate adaptive law. The unit characteristics included in our implementation include weights to connecting units, a threshold, residual activity, and a memory of activation history. As a method for representing the dynamic processes associated with residual activation energy and activation history, an event-based modeling method is used for convenience. By preserving the time and magnitude of the last activation as well as the mean and variance of the previous "interfiring" intervals, the LTM/STM parameters can be modified when necessary.

Short Term Memory—Temporal Credit Assignment. The unit parameters associated with the Short Term Memory or *attentional trace* reflect the relative activity state of each autonomous unit and its constituents. This characteristic is relative in that, as self-scaling units, it is relatively independent of the activity of the system as a whole. Consequently, a unit that "expects" to fire every three minutes, and fired a minute ago, is less "vigilant" than one that expects to fire every three seconds and fired two seconds ago. This concept of relative expectation is critical to successful adaptation in dynamic environments.

In our model, relative activity is represented in the current activity state and a number of parameters that preserve the unit's activation history. Residual activity, because it reflects the relationship between the current activity and a self-scaling rate of decay, is used for temporal credit assignment. Parameters reflecting the unit's firing history are stored to support both computation of the decay rate and STM adaptation directly.

Equation 1, the (negative) exponential function, has been chosen to represent the decay function because of its unique properties. First, since the exponential function is defined on the range 0 to ∞, for any time (t), which will always be positive, the function is defined and strictly decreasing. Second, the function can be normalized to a maximum value of 1 by eliminating the multiplier λ, leaving the exponential function shown in Equation 2. As an example, Figure 8 illustrates the relationships that exist between various values of λ and their "expected interfiring time." In order to generate a new

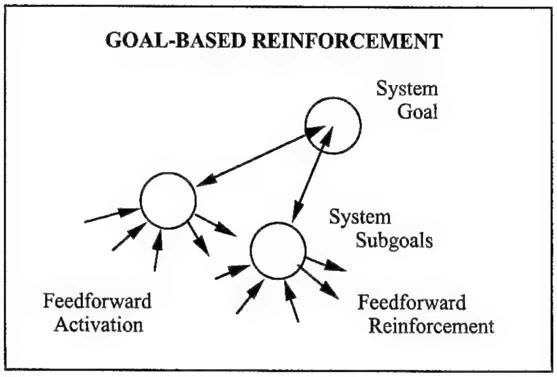

Figure 7. Propagation and Goal-Based Reinforcement

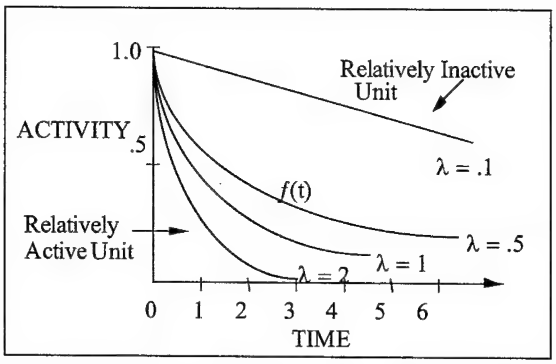

Figure 8. Activity(λ) and "Expected Interfiring Time"

activity parameter that reflects the influence of the current activation, an unweighted function has been chosen that generates a new λ' midway between the previous value and the last firing rate. This function, which is motivated by an assumption of limited local memory, places less weight on past history than that applied by Sutton and Barto (1981).

$$f(t) = \lambda e_{-\lambda} \quad I(0, \infty) \tag{1}$$

$$f(t)^* = e_{-\lambda t} \quad I(0, \infty) \tag{2}$$

The distinguishing characteristics of the proposed model include the representation of complex goal functions using multiple subgoals, an extensible architecture, truly autonomous memory units, and temporal credit assignment. The model is also unique in that it simultaneously supports rule-based, inductive reasoning in the presence of previously acquired information, as well as goal-based, deductive reasoning in the presence of new patterns of stimuli. In order to treat the information associated with dynamic activity, the model incorporates onlinr temporal reasoning and adaptation. By incorporating the temporal relationships between stimuli, the model incorporates a naive representation of the phase-characteristics of more complex control models.

These characteristics are used, in conjunction with reinforcement and inhibition signals, to maximize system subgoals directly, and system goals indirectly. A unique feature of this model is the role of the unit threshold filter ($[\theta]$) to control variance. This feature causes the units to be more sensitive to those patterns that have been correlated to reinforcement. This also makes the unit less sensitive to noise and therefore the system, as a whole, is more attentive to consistent patterns of behavior.

THE LEARNING EXPERIMENT

A two phase learning experiment was conducted to demonstrate and test the proposed model within a realistically complex environment. During Phase I, a network representation of a tactical decision criterion was trained offline, integrated into the CASTFOREM Command and Control submodel, and used to test the concept of a "neural" network, expert system simulation. In Phase II, the neural learning model, incorporating knowledge from the preceding rule-based network, was integrated into the simulation. Simulation runs were then made to compare force effectiveness with the preselected withdrawal criterion to a learned withdrawal criterion.

The scenario consists of a mounted defense against a mechanized attack as shown in Figure 9. The defending Green force and the attacking Orange force begin from initial positions as shown. The fundamental tactical problem for the Green force is when to begin withdrawal from their forward locations. To provide specific form to the defender's tactical evaluation, it is assumed that force performance should maximize the function: OL–GL. "OL" is defined to be kills of Orange (attacker) units and "GL" is defined to be losses of Green (defender) units. The learning task is to develop an internalized memory (set of rules) of the tactical relationships that contribute to a withdrawal

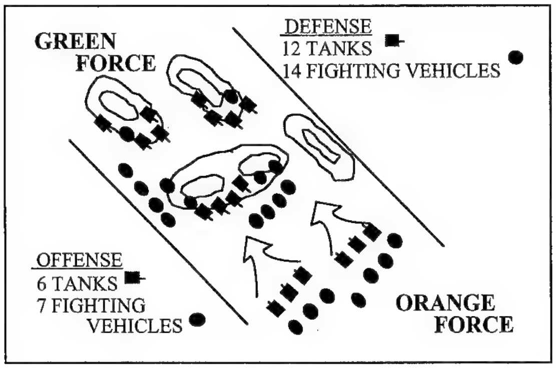

Figure 9. The Scenario

command that maximizes this tactical evaluation function.

Network Models

Two "neural" structures were developed for this CASTFOREM scenario. Both support a single tactical decision—when the Green force should withdraw. Three items of information are provided to both structures:

- Enemy Range (kilometers)
- Cumulative Orange Losses
- Cumulative Green Losses

The first network structure is a simple 3–2–1 open-loop, supervised classification model as shown in Figure 10. This non-adaptive model was developed to demonstrate the capacity of the network representations to duplicate the decision classification capabilities of traditional, symbolic structures such as the decision tables used in CASTFOREM. The unique aspect of the network structure is that it is trained to ignore Orange and Green Losses and only consider Enemy Range in implementing the order to withdraw.

Using backpropagation, the network was trained to a tolerance of less than 100 meters of range error with noise levels equaling the loss of all forces available. This demonstration indicated that, with adequate training, neural nets can provide representations of rule-based behavior that are as reliable (deterministic) as current symbolic methods. However, the computational expense required to achieve this level of reliability for an extremely naive knowledge base indicated that, while theoretically possible, the procedure may not prove feasible for realistic problems.

In the course of transitioning from Phase I to Phase II of the learning experiment, an interesting insight was gained. During pretesting of the learning model, the initial weights and thresholds used for the rule-based network were observed to be more resistant to adaptation than other weight sets that had been generated to satisfy the same decision at a lower tolerance to noise. The inference that was drawn was that learning is most expeditiously realized by initial network conditions that lie someplace between a random arrangement and one that generates deterministic behavior in the presence of varying levels of noise. To date, the focus of learning systems research has been on reducing the error associated with a given classification task by decreasing the system's sensitivity to noise. *However, that memory conditions that are more susceptible to noise are more efficient at learning implies that an adaptive model's sensitivity to noise is in conflict with a rule-based system's goal of behavioral consistency.*

The second network structure, Figure 11, expands the two-dimensional classification

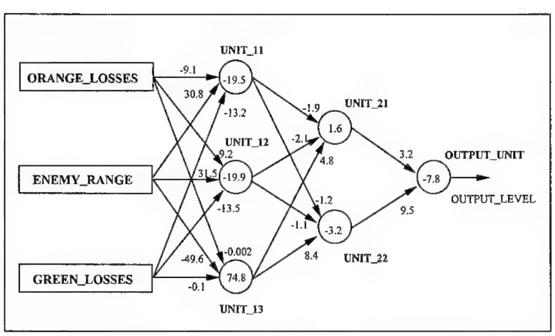

Figure 10. Classification Network–CASTFOREM Withdrawal

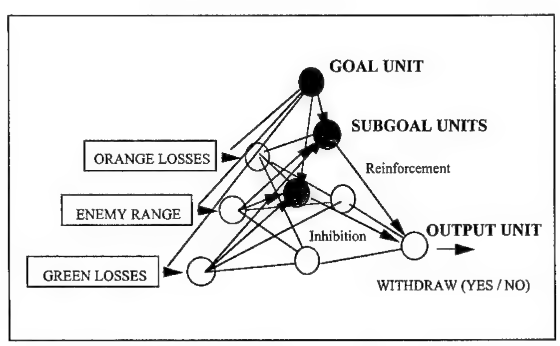

Figure 11. Adaptive Network

model to a three-dimensional, closed-loop, unsupervised, qualitative learning model. This structure, with goal-based performance evaluated in the third dimension, adds to the two-dimensional classification model links from input units upward to goal (black) and subgoal units (shaded) as well as reinforcement links down from these units. This model implements the logic discussed in the previous section on the Proposed Model.

The Results

In order to evaluate the performance of the adaptive model, three cases were run. In the Base Case, 30 replications of the scenario were generated with a deterministic withdrawal criteria (network or decision table). This data provided a basis for evaluating the influence of this fixed tactical rule on the performance of the Green force. The adaptive model was implemented in Case 2 and, responding to the influence of the most recent withdrawal decision on force performance, adjusted the withdrawal criteria accordingly. Because the adaptive replications (learning trials) were not independent, a third case was replicated with the final "learned" withdrawal criteria from Case 2 to determine the actual benefit from the learning. Because the learning system had stabilized on a deductive, or rule-based, mode, these replications were independent and suitable for statistical comparison to the Base Case results.

Base Case: Deterministic Withdrawal

Figure 12 reflects the pattern of cumulative Orange (attacker) and Green (defender) losses for the Base Case. The pattern of losses indicates that the Green force sustains significant losses during the first three minutes of the withdrawal and a later time window (18–20 minutes). The attacking Orange force suffers a relatively consistent pattern of losses so that at 35 minutes of battle time, losses stabilize at about eight for each side.

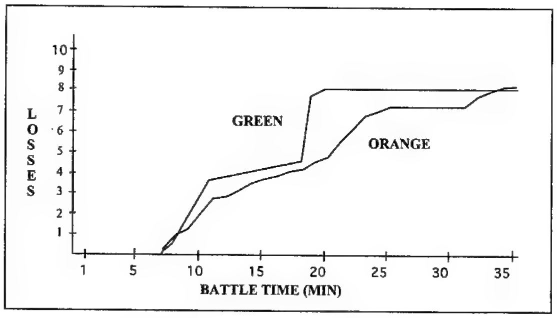

Figure 12. Base Case Losses

Case 2: Learning Withdrawal

Figure 13 represents the withdrawal time for the first 11 replications with the learning model. After replication 10, the Green force has learned that withdrawal contributes to losses and that performance (survival) is maximized by not withdrawing. The pattern of withdrawal times for the first 11 reps is nonmonotonic, indicating that learning takes place through trial-and-error, facilitated by the stochastic effects of the Monte Carlo simulation.

Case 3: Learned Withdrawal

In order to evaluate the improvement in force effectiveness attributable to this tactical change, replications 11–48, with the rule base stabilized without withdrawal, were isolated. The decision not to withdraw results in a measurable increase in early Orange Losses (Figure 14) and a consequent decrease in early Green Losses (Figure 15). These replications indicate that this strategy refinement results in a tacti-

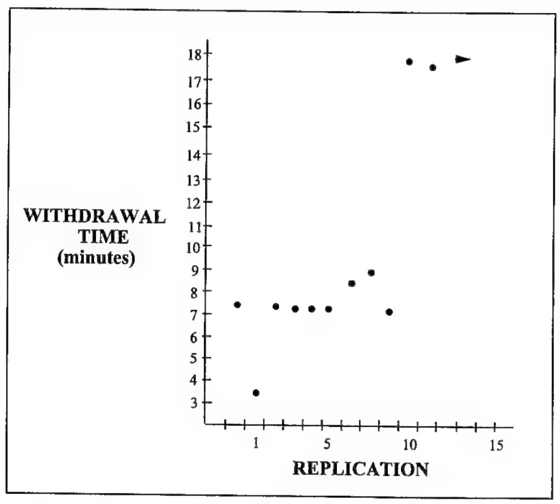

Figure 13. Learning GREEN Withdrawal Time

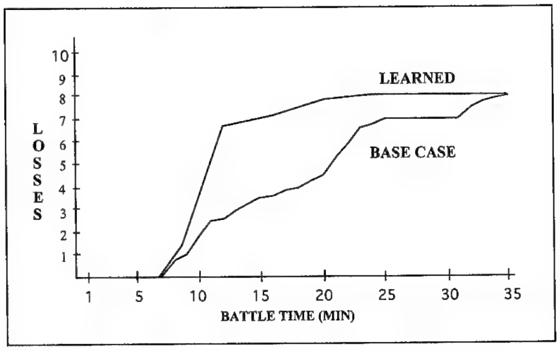

Figure 14. ORANGE Loss Comparison

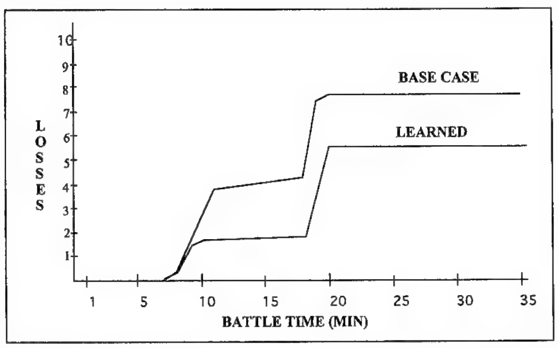

Figure 15. GREEN Loss Comparison

cally and statistically significant improvement in force effectiveness over the base case. The magnitude of this improvement is reflected in a reduction of average Green Losses from 7.7 to 5.4 (Figure 16).

SUMMARY

We introduced the motivation for this research as a response to the limitations of the current symbolic paradigm to support manageable and verifiable knowledge-bases for rule-based simulations being applied to dynamic and competitive problem domains. In this current form, expert system structures have been found to be difficult to develop, redundant, incoherent, and unverifiable. These limitations have acted to undermine the original motivations for knowledge-based simulations. Furthermore, they restrain the use of simulations to support more significant learning issues such as

- assessing behavioral influences on complex system performance (man-machine interface),

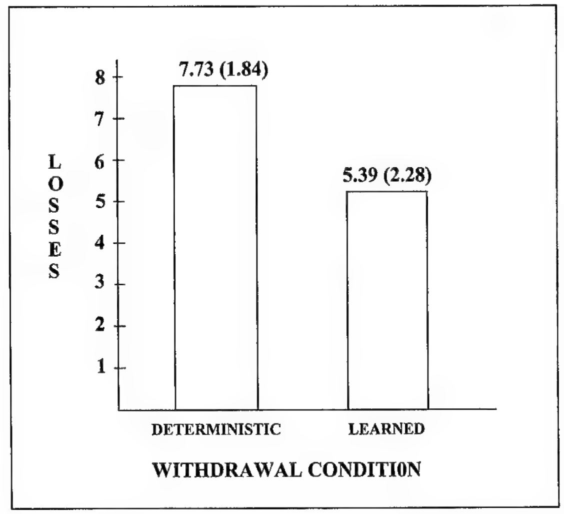

Figure 16. GREEN Loss Summary

- generating rules of behavior for developmental systems in general and those associated with complex or hazardous activity in particular, and
- developing, verifying, and updating intelligent system software for dynamic environments.

These limitations of current knowledge-based reinforcement learning systems have provided the motivation for a proposed model that is based on a truly autonomous unit. The unique characteristics of these units are that reinforcement signals are indistinguishable from other signals, and that unbounded weight growth is controlled by a uniquely adaptive threshold filter that acts to control each unit's signal-to-noise ratio. These unique memory units support a general model of intelligence that

- is naturally extensible in that modifying the input/output sets or system goal should not require complete regeneration of memory,
- represents complex goal functions supported by multiple subgoals that act to maximize the objective function, and
- supports rule-based, deductive reasoning in the presence of environmental activity that is consistent with expectation as well as goal-based, inductive reasoning in the presence of uncertainty—unfamiliar patterns of activity.

While the specific purpose of the prototype is to address the limitations of current knowl-

edge-base simulations, it also aspires to support a more powerful model of general intelligence that would allow intelligent simulations to generate and validate knowledge-bases for developmental hardware and software systems. The results of the learning experiment showed that this model is not only capable of supporting effective strategy refinement, but converging to stable, rule-based behavior quickly and efficiently without unbounded weight growth.

Future Applications

The preceding observations cause us to be optimistic about using complex, computer simulations for a variety of learning tasks in both military and nonmilitary environments. First, as the results of this learning experiment show, the adaptive procedure can be used to determine the maximum tactical advantage that can be achieved in a given scenario. This capability is extremely important to making sound engineering decisions among competitive technological opportunities.

Second, the procedure clearly holds the promise of isolating potential improvements in "how to fight" strategies for emerging systems. While the limited transparency of existing network programs may limit their flexibility, automated procedures for isolating the tactical changes that contributed to improved performance are clearly feasible.

Third, as the Department of Defense and industry increase their reliance on automated decision aids, adaptive simulations should provide a powerful capability for developing, validating, and updating the associated firmware for changing environments. The significance of this capability is compounded by limitations in extracting essential, but "inaccessible," knowledge from subject matter experts.

Finally, as a training tool, "smart" simulations with adaptive opponents may significantly enhance the value of computer wargames. As synthetic opponents "learn" and respond effectively to the tendencies of one or more human opponents, they will force students to develop a more robust understanding of their environment. Within the context of doctrinal development, this procedure could be extended to supporting objective methods for evaluating alternative behavioral strategies.

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Locational Analyses of Military Intelligence Ground Facilities

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INTRODUCTION

The purpose of this work is to develop a normative additive utility model to determine where best to locate military intelligence ground facilities. Actually, the model and the framework suggested in this paper can also be employed to analyze alternative civilian systems, such as traffic control systems.

The location of military intelligence facilities has a significant impact on the value of future events. These facilities are responsible for producing intelligence under different states (peace, stationary conditions, and war). Military intelligence systems can be classified according to a variety of attributes: the nature of their location (e.g., on the ground, in the air, or in space); and the nature and the focus of their mission (e.g., operational, tactical, or strategic). The mission definition may depend on given features of the system; for example, the distance of the system from enemy lines, its equipment, the complexity and magnitude of its operations, human skills, and the hierarchy of the system at the organizational level are considered for classification of the mission level or type. The model suggested here is applicable to ground facilities of all types.

The system under consideration may have the capabilities to produce a mix of intelligence products. At each facility, this mixed product is generated by various sources, including verbal and non-verbal electronic signals, visual electronic signals, and visual non-electronic information. The system has the ability and capacity to absorb, store, process, and distribute the intelligence within and out of the system's boundaries. The quality and quantity of the intelligence that the system receives and produces in a given period (e.g., a day) depends on the location of each of its facilities relative to the enemy target's positions, its level of technology and human-machine interfaces, the dynamic patterns of enemy movements, capacities, and nature, and the scale and complexity of the enemy's systems.

Studies concerned with the interface between operations research and military intelligence, or O.R.-intelligence, are generally classified, and locational military intelligence decisions have seldom been studied in the unclassified O.R. literature. Recently, Kreimer and Mehrez (1994) and Hersh, Mehrez and Zangwill (1985) analyzed the operational aspects of air intelligence systems, whose role in the modern battlefield is becoming more and more significant. The present study, however, is focused on locational decisions of ground intelligence facilities.

In practice, intelligence locational decisions are coordinated with other military and civilian agencies. There is a variety of processes by which these decisions are made. The authors observed that, depending on time and space constraints at the first stage, a screening procedure is implemented to select a candidate set of sites to locate intelligence facilities. Various factors are taken into account, such as: environmental and physical conditions, and military risk (the possibility of the enemy damaging the facility) at a given site. In general, then, screening analyses are concerned with the features of each site. Interactive effects generated between or among sites have previously been neglected and have not been evaluated in detail at this stage.

Interactive effects between facilities at different sites can take place in different ways. For example, to identify the location of an enemy target, signals or directional signals from at least two sites or sources are required. A necessary condition for the existence of a directional signal for most technologies is that a sight line between the considered site and the enemy target must exist (this line-of-sight can be verified by various methods). The magnitude of the angle (in degrees) formed by the directions from the two sites toward the target affects the quality of the signals generated by each site and the capability of identifying the target in a statistically reliable way. As the number of candidate sites increases, the ability of military experts to process the information required to optimize locational decisions is diminished. In particular, it is difficult for a human expert to evaluate and analyze interactive effects on attributes which depend on the locations of two or more sites relative to a variety of targets.

Intelligence locational decisions at any level form a part of the entire complex structure of the intelligence resource allocation decision-making process. This process is similar in its components to other resource allocation processes that take place in private and in public sectors (see, e.g., Berahas, 1981; Bertalanfy, 1968; Buzzacott and Yao, 1986; Forrester, 1968; Mitroff, Emshoff and Kilmann, 1979; for further materials on this subject, see Mehrez and Enrick, 1989, and the references provided therein). Both at the strategic level and under stationary conditions, decisions concern which types of technology and products should be developed or purchased to meet future possible threats. Tactical deci-

sions are concerned with the allocation of intelligence resources (human, equipment, facilities) by zone or region and per period. As already noted, facilities can also be classified as strategic, tactical, or operational, depending on various attributes. In sum, the tactical decision is concerned with the product mixture.

The scheduling of systems and sub-systems is determined at the operational level. Recently, Mehrez, Speirs and Brimberg (1994) formulated and solved an operational intelligence problem motivated by observation of an intelligence ground system. The main feature of such a problem that differentiates it from industrial marketable production systems is the non-additive nature of intelligence output. In their study, Mehrez et al. (1994) did not address the locational decision problem, but, rather, assumed the locations of the facilities to be fixed and known. This study addresses the locational decision problem explicitly.

A deterministic, static, uncapacitated, integer programming model is formulated in the next section to locate intelligence facilities. The deterministic structure is evaluated by an additive utility function which takes into account the existence of multiple enemy targets in the region or area under the responsibility of the decision-maker. In the third section, the application of the model is illustrated by an example. The results of a computational study, where several hypothetical instances of various configuration are solved, are discussed in the fourth section. Finally, further possible extensions are proposed.

THE MODEL

In this section, an uncapacitated optimization model is developed for the intelligence facility-location problem. The model is 'uncapacitated' because there are no restrictions on the number of targets that can be monitored, or on the volume of information that can be absorbed by a facility. Capapcity considerations are discussed in the Extensions Section. The planning problem involved at least three types of decisions: 1) in which sites to locate facilities, 2) what targets to monitor, and 3) given the facility locations, which pair of facilities should monitor each of the targets. Considering the restriction on the number of facilities that can be opened, the objective of the model is to maximize the cumulative utility of the monitored targets. The types of decisions involved make the intelligence-facility location problem a member of the well-studied class of discrete location-allocation problems (see e.g., Brandeau and Chiu, 1989; Francis, McGinnis and White, 1992; Mirchandani and Francis, 1990). Following the model statement, its position within the location-allocation literature will be discussed.

As explained earlier, not all targets can be monitored from a given site due to technological limitations of sensing and monitoring equipment. Distance is one factor; a target may be too far away to be sensed from a particular site. Topography is another factor; the altitude gap between a site and a target may prohibit target sensing from the site. In addition, current technology requires, in most cases, visibility of the target from the site; i.e., existence of a sight line between both. Satisfaction of this requirement depends on topographical structure. Current technology also requires, in most cases, monitoring each target from two distinct sites, such that the angle formed between the two sites, whose vertex is the target, lies within a certain range of magnitude.

Following this discussion, the notion of an admissible triplet can be defined and used. An admissible triplet contains a target and two sites, such that the target can be monitored from the two sites at a satisfactory quality level. To put it formally, let the targets be indexed by $j = 1, 2, \ldots, m$ and the contemplated sites be indexed by i, $i = 1, 2, \ldots, n$. The model assumes that a list, designated T, which contains all admissible triplets, has been constructed: $T = \{(i_1, i_2, j): i_1, i_2 \in \{1, \ldots, n\}, i_1 \neq i_2, j \in \{1, \ldots m\}\}$. To facilitate model formulation, let $B_i = \{(k, j): k \in \{1, \ldots, n\}$ and either $(i, k, j) \in T$ or $(k, i, j) \in T\}$ and $A_j = \{(i_1, i_2): (i_1, i_2, j) \in T\}$. A_j, denoted the observing set of target j, is the subset of site-pairs from which this target can be monitored, and B_i consists of the complementary parts of the subset of triplets which contain site i. The following model, denoted $P1$, selects p (out of n) sites to locate intelligence facilities, such that the cumulative utility of the monitored targets is maximized, where w_j is the utility of monitoring target j.

$$(P1) \quad Max\ v = \sum_{j=1}^{m} w_j \left[\sum_{(i_1, i_2) \in A_j} x_{i1,i2,j} \right]$$

s.t.

$$\sum_{(i_1,i_2)\in A_j} x_{i1,i2,j} \leq 1 \quad j = 1, \ldots, m \tag{1}$$

$$\sum_{(k,j)\in B_i} x_{i,k,j} - My_i \leq 0 \quad i = 1, \ldots, n \tag{2}$$

$$\sum_{i=1}^{n} y_i \leq p \tag{3}$$

$$x_{i1,i2,j} \geq 0, \quad y_i = 0 \text{ or } 1 \tag{4}$$

The variables y_i indicate whether a facility is located at site i, $y_i = 1$, or not, $y_i = 0$. Constraints (1) imply that each target is assigned to, at most, a single pair of facilities, while constraints (2) guarantee that targets are monitored only from sites where facilities have been located. Factor M in constraints (2) is a big number, the number of elements in B_i or, more tightly, the number of elements in the set $J_i = \{j: \exists\ (k, j) \in B_i$ for some $k\}$. Constraint (3) ensures that no more than p facilities are located. Altogether, $m + n + 1$ constraints.

The model is similar to the covering model (Toregas, Swain, ReVelle and Bergmen, 1971), or, more precisely, to the maximal partial-cover model (Church and ReVelle, 1974), and its solution is, in fact, a maximal partial-cover. However, a single resource for each destination is sufficient for the covering models, while two resources are required simultaneously for each target in $P1$. The simultaneous coverage requirement distinguishes also between $P1$ and the back-up covering model (Hogan and ReVelle, 1986), which seeks coverage of a destination by two resources, as well, but not simultaneously. Thus, covering techniques are not applicable to solving $P1$. Also, the structure of constraints (1) and (2) resembles network constraints (e.g., see Bazaraa and Jarvis, 1977), and network flow models are well solved integer programming models. In fact, the model can be represented as a network of three layers of nodes, as shown in the next section. However, unlike network flow models where each variable appears twice in the constraint matrix, each variable in $P1$ appears three times, thereby ruining the network structure.

Note that despite the discrete nature of the decision involved and the fact that the constraint matrix in not total unimodular, the variables $x_{i1,i2,j}$ need not be explicitly specified as integers. To see that, suppose sites r and s have been selected. The formulation of constraints (2) allows the allocation to r and s of all targets that can be monitored by r and s. In a formal manner, $x_{r,s,j}$ can be set to 1 for all $(r, s, j) \in T$. Suppose also that another site, say q, is also selected and that targets exist which can be monitored by q and r as well as by r and s. Under these circumstances, allocation of the relevant targets has no effect on the final outcome and is, thus, made arbitrarily. In general, no variable $x_{i1,i2,j}$ can have a positive value unless both y_{i1} and y_{i2} equal 1. Once this condition is satisfied, the exact value of $x_{i1,i2,j}$ is of less importance as long as their sum equals 1 for each relevant j and this is taken care of by the positive weights, w_j, in the objective function. These observations significantly affect the computational complexity of $P1$, which is an optimization model of integer decision variables. It is well known that integer programming models are hard to solve in terms of required computing resources—time, mainly, and memory, too—and computing resource requirements grow exponentially in the number of variables in the model. The observations above imply that $P1$ is a mixed-integer (rather than pure integer) model, for which the solution effort is affected primarily by the number of integer variables and much less by the number of other variables. The number of integer variables in $P1$ equals the number of contemplated sites, n, which constitutes just a small portion of the total number of variables in the model (which includes, in addition, the sum of the numbers of elements in each of the sets A_j). The use of the model is illustrated by an example in the next section and computational issues are further discussed in the fourth section.

AN ILLUSTRATIVE EXAMPLE

For clarity of presentation, a small example has been constructed. The actual capabilities of the model are demonstrated by the computational study in the next section. The example consists of seven targets and four candidate sites, but only two facilities are available. Thus, two of the four sites have to be selected to locate the facilities in order to maximize the cumulative utility of the monitored targets. The data is detailed in Table 1, including the utility of each target and the pairs of sites from which it can be monitored.

The locational decision model $P1$ can be represented as a network, as illustrated in Fig-

Table 1. Data for Example

target (j)	1	2	3	4	5	6	7
utility (w_j)	2	8	4	2	4	1	8
observing set (A_j)	1, 2	1, 2 1, 3 1, 4 2, 3	1, 3 2, 3 2, 4	2, 3 2, 4 3, 4	2, 4 3, 4	2, 3 3, 4	1, 4 3, 4

ure 1 for the example data. The nodes numbered 1–4 on the left represent the candidate sites, while the nodes 1–7 on the right represent the targets. Each site-pair in Table 1, along with the corresponding target, constitute an admissible triplet. Thus, the nodes in the middle, which correspond to site-pairs, are connected to both sites in the pair and to all targets that can be monitored from the two sites in the pair.

A feasible solution to the model $P1$ is a sub-network induced from the network in Figure 1, such that, if the sub-network contains a target-node, that node is connected to at least one site-pair node that is connected to both site nodes of the corresponding pair of sites. The availability of only two facilities, in the example, implies that the sub-network contains a single site-pair node. For example, the site-pair

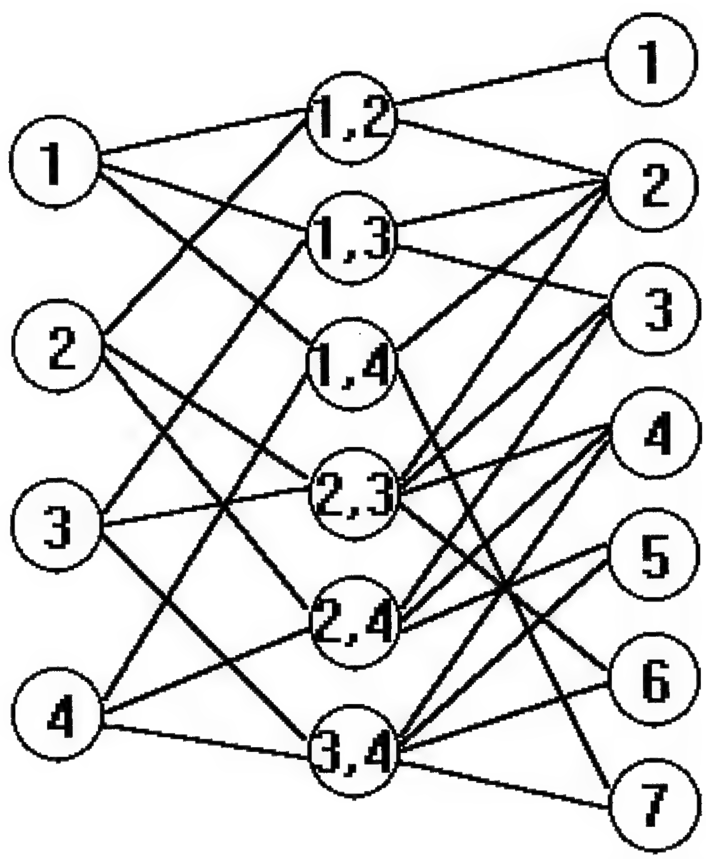

Figure 1. Network Representation of the Intelligence Facilities Location Problem

node (2,3) can be selected with, of course, the site nodes 2 and 3 and the target nodes 2, 3, 4, and 6. The objective of the model is to maximize the cumulative utility of the targets included in the sub-network. In this example, with two facilities available, the optimal solution is to locate the facilities in sites 1 and 4 and monitor targets 2 and 7 with cumulative utility of 16. This value is higher than the cumulative utility (15) of the four targets that can be monitored from sites 2 and 3, and from any other two sites.

Clearly, if more than two facilities are available, more site-pair nodes can be selected. Consequently, the determination of the optimal solution is more complex and requires the use of more sophisticated and preferably computerized tools, as described in the next section.

COMPUTATIONAL DEMONSTRATION

The goal of this paper is to demonstrate the applicability of logistic design tools, O.R., etc., to military intelligence design tasks. The demonstration began with a formulation of an optimization model for a representative task; solving the model and interpretation of the results then followed. We make no claim that the solution technique employed for this study is the most efficient one could select. On the contrary, to demonstrate the applicability of our approach, we aimed at a reasonable solution time using readily available tools. Consequently, a commercial optimization software, CPLEX™ has been used in a straight-forward manner, on an IBM-RS6000/550 computer.

Three data sets were randomly constructed for the study. The number of contemplated sites in each set is $n = 20$, while the number of targets varies: $m = 60$, 90, and 120. The triplets (i_1, i_2, j) were randomly sampled, such that the number of elements in sets A_j is an average of 10. Each data set was solved for four different values of the number of facilities to locate ($p =$ 4, 6, 8, and 10) and the results of the 12 executions are presented in Table 2. Descriptive information about the instance is presented in the four columns on the left: in the first, left-most, column, the number of targets is specified; in the second, the sum of the element numbers in the sets A_j, i.e., the number of $x_{i1,i2,j}$ variables; the sum of all target weights, the maximum objective value, is given in the third column; and, the number of facilities to locate is in the fourth. The output is presented in the other columns: the optimal objective value in the fifth; the percent coverage (i.e., optimal value/sum of target weights) in the sixth; and in the seventh, the right-most, column, the total CPU time, in seconds, is reported.

Consider first the fourth, fifth, and sixth columns and notice the impact of the number of available intelligence facilities on the quality of the outcome. The more facilities that are available (larger p) the higher is the cumulative utility, but the marginal improvement diminishes as illustrated in Figure 2. These results are quite natural and are presented here to validate the model by showing that it behaves in an intuitively expected fashion. Note, however, the closeness of the coverage curves in part (b) of Figure 2, which indicates that the number of

Table 2. Computational Results

m	$\Sigma\lvert A_j\rvert$	Σw_j	p	v^*	% coverage	CPU
			4	540	53.1	254
60	698	1016	6	834	82.1	965
			8	969	95.4	600
			10	1016	100.0	19
			4	700	52.7	660
90	1127	1328	6	1093	82.3	2679
			8	1292	97.3	2343
			10	1328	100.0	89
			4	840	47.7	950
120	1382	1762	**6**	**1399**	79.4	3477
			8	1665	94.5	2965
			10	1752	99.4	722

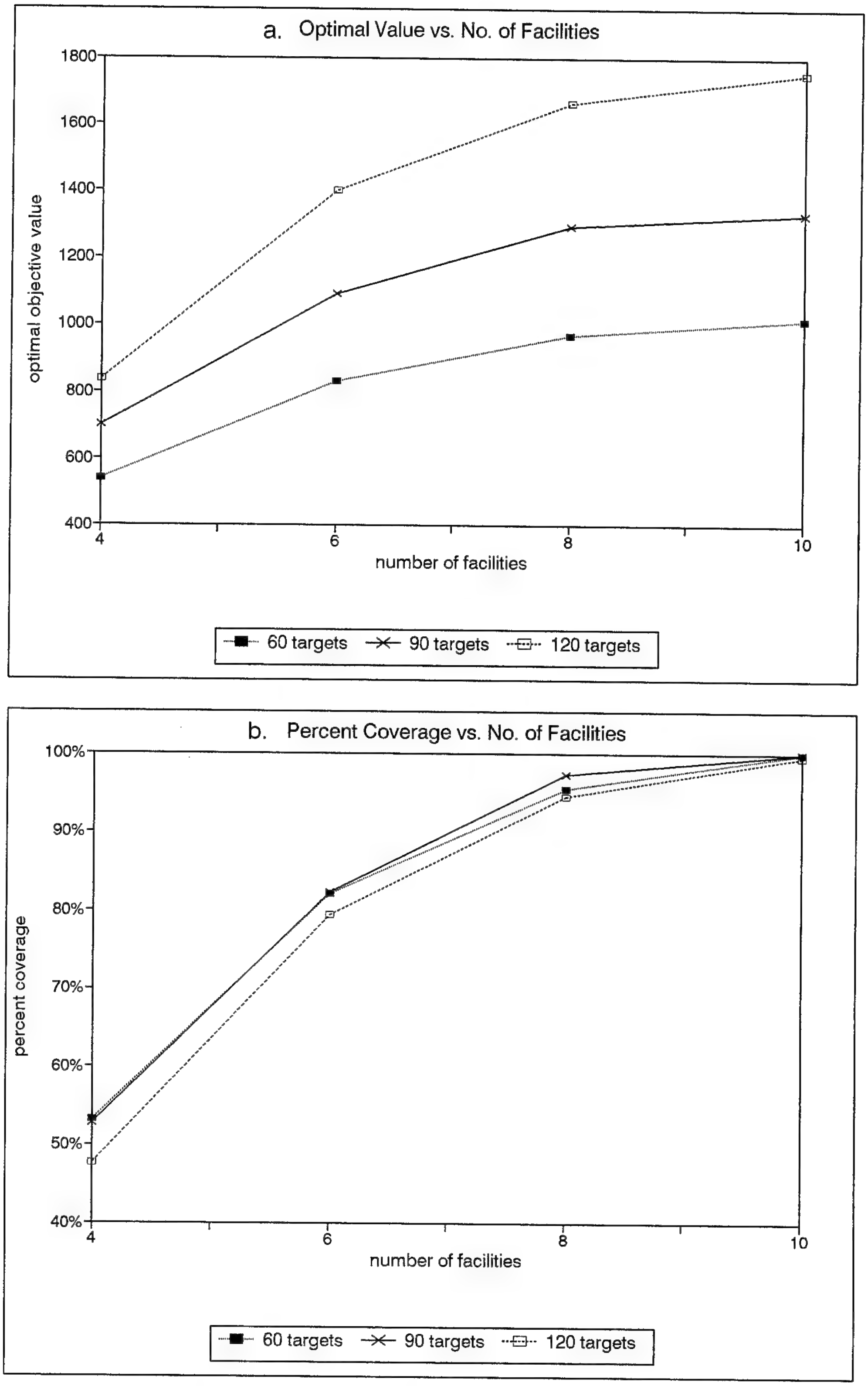

Figure 2. The Intelligence Facilities Location Problem—Computational Results

targets has no effect on the percent coverage. Less intuitive are the levels of coverage achieved. Using only 30% (6/20) of the potential sites, the objective value is about 80% of the maximum possible, and practically complete coverage (99.4% in the worst case) is accomplished when 50% of the sites are used. Even when less facilities are available (only 20% of the candidate sites can be used) about 50% coverage is attained. This result is even more impressive considering the much larger number of targets and the requirement of double coverage for each target. The advantage of the model $P1$ is best illustrated by the highlighted cells (shadowed characters) in Table 2, where 80% coverage of 120 targets is accomplished using only 6 intelligence facilities (5% of the number of targets).

Once the quality of the outcome of the model has been shown, there remains the question of the required effort. The answer is provided by the solution times listed in the last column of Table 2. In the worst case, 3,477 second (a little less than 58 minutes) were required to construct the solution and prove its optimality. Considering the solution quality, this is a reasonable time for a task which is performed even on a daily basis, and the intelligence facility location task is performed less frequently. In addition, a general purpose optimization software was used for this study, that has been installed on a computer which is not very fast—Spec. 92: integer 36.2 and floating point 83.3. Efficiency of the solution process can increase significantly by using a stronger platform and specific tools more suitable for the model $P1$.

EXTENSIONS

The model $P1$ proposed above is based on certain assumptions that can be relaxed to extend the model's applicability. Some of these extensions are discussed in this section.

First, it is assumed that all sites are homogeneous in terms of target observability, as reflected by the single index of the utility factors w_j which implies that these factors are independent of the monitoring sites. A triple index can be used, $w_{i1,i2,j}$, to extend the model to account for differences in the quality of the intelligence produced due to a facility location. This modification has no impact on the attributes of model variables, in the sense that the allocation variables $x_{i1,i2,j}$ can still be considered continuous. Integral values are guaranteed in an optimal solution because the facilities are of unlimited capacity; hence, each target will be assigned to the selected pair of sites of highest observability (maximum utility).

Second, the number of facilities p is assumed to be fixed in the model, while, in reality, the number of facilities in each region can be altered by moving facilities between regions. The model can be modified to consider this issue by replacing constraint (3) with a "cost" term in the objective function: $-c\Sigma_i\, y_i$, where the coefficient c represents the utility that can be gained if the number of facilities decreases by one (e.g., a facility is moved to another region). This modification, too, does not affect variable attributes, as explained above.

Third, facility capacities can be considered, since it is often the case that the number of targets that can be monitored by a facility is bounded by technological constraints, manpower, etc. Limited monitoring capacity may significantly affect the solution structure and quality. For example, we have highlighted the case where 80% coverage of 120 targets has been accomplished by 6 facilities only. This implies an average of 40 targets for each facility (since each target has to be monitored by two facilities), which may exceed the available capacity. Further, the solution of an uncapacitated model may be highly imbalanced, such that many targets are allocated to one, or few facilities, in excess of their capacities. Consequently, when capacity constraints are imposed, solution quality declines and more facilities might be required.

Capacities can be considered independently of the first extension of differential observability, in one of two ways: fixed, which constitute a part of the model parameters, or variable. In the basic formulation given above, fixed capacities can be imposed by replacing the big-M coefficients in constraints (2) with the capacity limit; i.e., the maximum number of targets that can be monitored by a facility. This adjustment works also for the extended model, in which the number of facilities is a decision variable. However, the number of facilities is a capacity measure, too. Hence, a more general formulation is one which considers both the number of facilities and the capacity of each facility in conjunction. The principle change is the interpretation of the location variables y_i, which, originally, represented the dichotomic

decision: is site i selected or not. This definition can be extended to include also the capacity allocated to the facility at site i. While a zero value of y_i implies, in both cases, that no facility is located at the site, a positive value should be interpreted according to the specific formulation. The extended definition implies that the variables y_i are no longer restricted to the values zero or one, but may take any non-negative value. Consequently, the big-M coefficients in constraints (2) can be eliminated. Capacity allocation may be considered either as a constraint or as a decision. As a constraint, the current constraint (3) with the extended interpretation of y_i, and p denoting the total capacity available, will do. As a decision, a "cost" term $-\Sigma_i c_i y_i$ can be added to the objective function instead of constraint (3), as explained above.

Unfortunately, modifications required to account for capacity considerations ruin the structure of the model, thereby making it much harder to solve. The change of attributes of location variables and the consequent adjustment of constraints (2) require that integrality of the allocation variables $x_{i1,\ i2,j}$ should be imposed explicitly. The implication can be illustrated by the data in Table 2. Under the original formulation, each instance involves 20 integer variables plus $\Sigma|A_j|$ continuous variables; while in a capacitated model all variables are integer: 718 for the sixty target instances, 1147 for the ninety target instances, and 1402 for the hundred and twenty target instances. These are destructive changes in terms of solution time and dictate the use of alternate approaches to solving the model.

CONCLUSION

In this paper, the applicability of the optimization approach to address the intelligence facilities locational decision problem has been study. A static, deterministic, optimization model has been formulated for the locational decision problem of ground intelligence facilities. The model aims at the selection of a small subset of sites from a larger set of candidate sites, so as to locate intelligence facilities such that the cumulative utility of the monitored targets is maximized. The application of the model has been illustrated by an example. The applicability of the optimization approach has been demonstrated via a computational study and through a discussion of possible extensions that enables one to handle a large variety of configurations related to the intelligence facility locational decision problem.

The quality of designs obtained by solving the model strongly motivate the development and application of specific methods, algorithms, and techniques in order to improve the efficiency of the solution process. Further, developments in this direction are necessary for the implementation of more general extensions of the model, capacity concerns in particular. There exists a host of efficient procedures for combinatorial optimization, including some that are especially suitable for capacitated model, which may be incorporated into an effective and efficient scheme to solve the intelligence facility locational decision problem.

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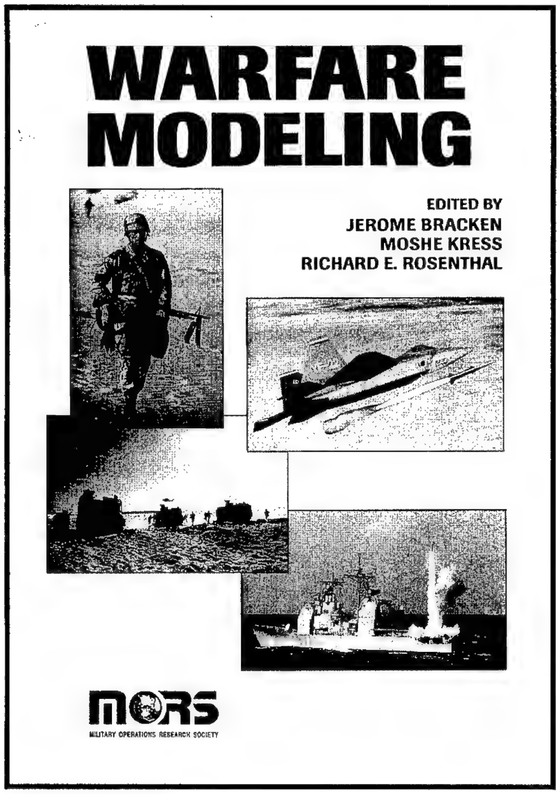

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Scheduling of Military Vehicles Through the Deliberate Nuclear, Biological, and Chemical Decontamination Process

Georgia-Ann Klutke

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Major, U.S. Army Chemical Corps and Battalion S3 (Operations Officer) Fort Hood, Texas

INTRODUCTION

The nature of future conflicts may require the United States Armed Forces to operate in battlefield environments contaminated by nuclear, biological, or chemical (NBC) agents. The U.S. Army Chemical School at Fort McClellan, Alabama, is responsible for developing decontamination procedures for Army personnel and equipment. According to U.S. Army field manuals NBC Contamination Avoidance FM 3-3 (1986), NBC Decontamination FM 3-5 (1985) and NBC Protection FM 3-4 (1985), the decontamination of personnel and equipment is performed at two levels. *Partial decontamination* emphasizes decontaminating just enough to sustain operations and to keep fighting rather than ensuring a contamination free environment. *Detailed decontamination* includes both detailed troop decontamination and detailed equipment decontamination, and consists of procedures that reduce contamination to a level that permits soldiers to operate for extended periods without wearing protective clothing or equipment like a mask and gloves. Because of the considerable time and logistical requirements of detailed decontamination, detailed decontamination will generally not be performed until a unit, battalion size or larger, is pulled from the battle for reconstitution; as a result, it is imperative that the process be completed as quickly as possible.

The U.S. Army currently operates the decontamination process essentially on a first-come-first-served basis. Consequently, company vehicles are often decontaminated by platoon, with platoon vehicles grouped by squad. A squad's vehicles are usually processed in the order in which they arrive at the decontamination site, which is based on security requirements for the tactical road march from the battle front rather than on processing time considerations. The objective of this study is to provide a scheduling decision support system that can be used by NBC decontamination units in the field to reduce the total decontamination time (in manufacturing parlance, the makespan) for all vehicles in a battlefield unit.

This study was conducted using the U.S. Army's heavy divisions (mechanized and armored divisions), which are comprised of 56 different company-sized organizations. The equipment to be decontaminated consists of the vehicles (wheeled, tracked, or a wheeled vehicle with its trailer) in the company's command. Each company has in its command up to 130 different vehicles; they vary dramatically in size from a 1/4 ton jeep to a 60 ton M1 combat tank (U.S. Army Staff Officers Field Manual FM 101-10-1/1, 1987). In order to support its particular mission, each company has a different number and mix of vehicles. For our purposes, all vehicles of the same type (e.g., armored personnel carriers) will be considered to have statistically identical processing times, with individual differences due to statistical variation.

Depending on the form of contamination (nuclear, biological, or chemical), the decontamination line consists of from four to six different stations arranged in series. Figures 1 and 2 show, respectively, the processing stations and order of processing for detailed biological/chemical and nuclear equipment decontamination. Each box represents a decontamination station, which consists of a single server manned by one or more soldiers. Detailed troop decontamination is performed in a similar fashion, but is not considered in this study. The equipment decontamination line is staffed by a crew of 12 soldiers from the chemical unit in charge and 5 specially trained soldiers from the contaminated unit. While more than one soldier may be assigned to a given station, vehicles are decontaminated one at a time (i.e., serially), and the assignment of soldiers to each station remains constant throughout the process. The processing time used in the study is the amount of time required for a vehicle to be decontaminated at a station.

We model the NBC decontamination process as a non-preemptive flow shop with zero intermediate storage (Dempster et al., 1982). A non-preemptive flow shop consists of a group of jobs (in our case, vehicles) that require processing (decontamination) on a set of machines (decontamination stations). There are no precedence constraints on the jobs, and all jobs must visit the machines in the same order. A job is not allowed to pass (preempt) other jobs; the order in which jobs finish their processing is the order in which they began their processing. When a job finishes processing on a machine, it begins processing on the next (downstream) machine if that machine is idle; otherwise, it waits on (*blocks*) the machine on which it has finished processing. Thus in a flow shop with no intermediate storage, a machine can be in one of three states: busy, idle, or blocked. A *sequence* or *schedule* consists of a list of jobs and the order in which they are to be processed. In a flow shop with n jobs, a schedule is a permutation of the job labels

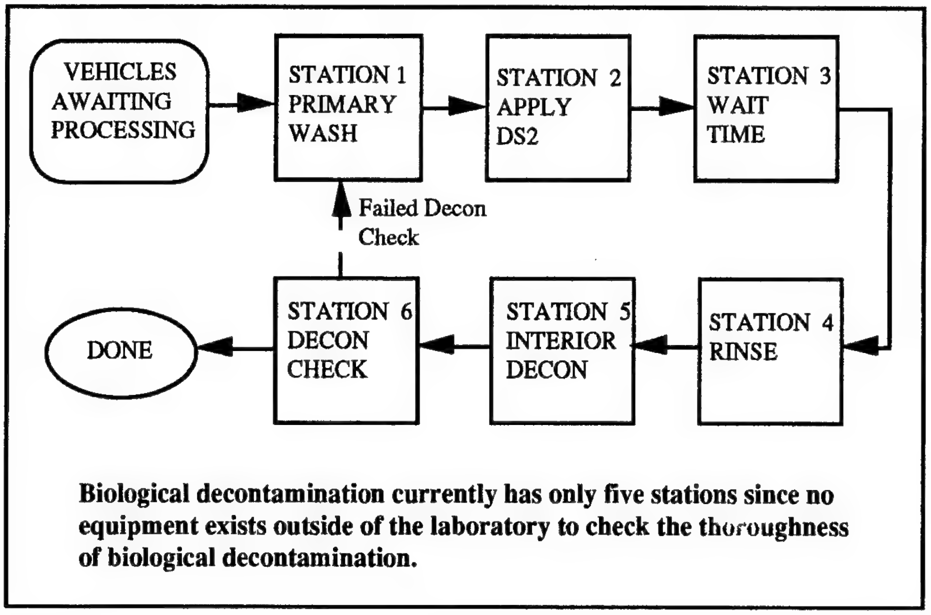

Figure 1. Flow Diagram of Detailed Biological/Chemical Equipment Decontamination

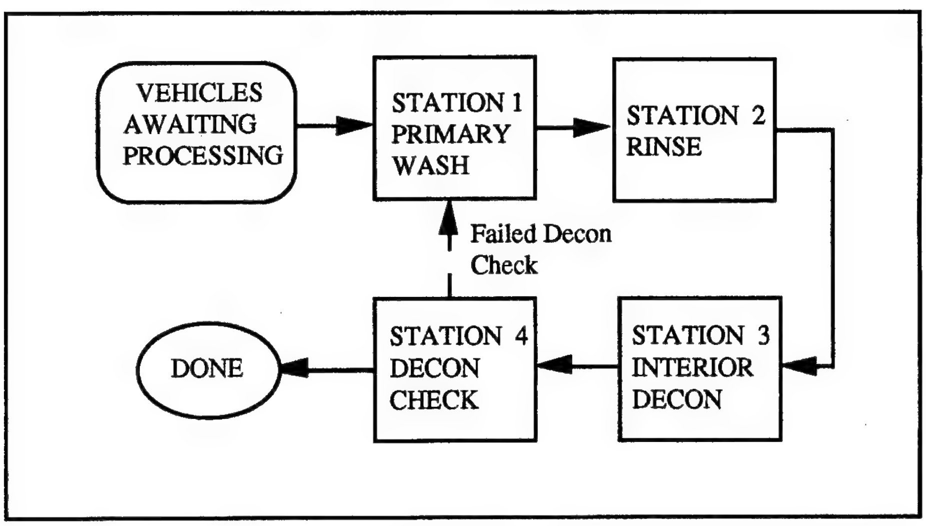

Figure 2. Flow Diagram of Detailed Nuclear Equipment Decontamination

$(1, 2, \ldots, n)$, e.g., $(j_1, j_2, \ldots, j_n)$. Let us denote a particular permutation of $(1, 2, \ldots, n)$ by π_n, and the set of all such permutations by Π_n. Note that there are a total of $n!$ possible permutation schedules. The *makespan* of a schedule is the amount of time required to complete the entire group of jobs; thus the makespan is the sum of the individual job processing times and the delays due to blocking. In our problem, makespan is the total amount of time required to decontaminate all the vehicles of an entire unit. By an *optimal schedule* we mean a schedule that minimizes (in some mathematical sense) the makespan among all possible schedules.

Let $C_1(\pi_n), C_2(\pi_n), \ldots, C_n(\pi_n)$ be the completion times of the n jobs for the schedule π_n. Then the problem of minimizing the makespan in the flow shop can be stated mathematically

as follows:

Minimize over all $\pi_n \in \Pi_n$:

$$C_{MAX}=\mathrm{Max}(C_1, C_2, \ldots, C_n)$$

RELATED WORK

When job processing times are assumed to be known constants, the problem is deterministic, and this version of the problem has been well-studied in the literature. Johnson (1954) provided one the first exact results for this problem; in a classic paper, he gave an algorithm (Johnson's rule) for finding the schedule that minimizes the makespan in the 2-machine flow shop. The deterministic *m* machine version of this problem is known to be NP-complete for $m > 2$ (*Garey and Johnson*, 1979, *p.* 241), and many heuristic solution strategies exist (cf. Garey and Johnson 1979). However, the salient features of the problem considered in this paper, namely the random processing times, take it outside the realm of the deterministic case. Our aim here is to develop and examine procedures that yield good schedules in the presence of variability in processing times.

It has only been in the last decade that the stochastic flow shop with no intermediate storage has received attention. If the processing times of the jobs are random variables, then so, clearly, is the makespan, and the mathematical sense in which the makespan is to be minimized needs to be specified. Stochastic ordering is a common way of comparing random variables (Shaked and Shanthikumar, 1994). Under the expected value ordering, a non-negative random variable X is less than another random variable Y if $E[X] < E[Y]$. Under the strong stochastic ordering, X is less than Y if $F(x) > G(x)$ for all $x \geq 0$, where $F(x) = \Pr(X \leq x)$ and $G(x) = \Pr(X \leq x)$. Under the non-overlapping ordering, X is less than Y if $F(x) > G(y)$ for all $x, y \geq 0$ (i.e., $\Pr(X \leq Y) = 1$).

Let P_{ij} be the processing time of job i on machine j (since machines are identical by assumption, P_{ij} and P_{ik} have the same distribution, and hence the same mean μ_i, for each i and all j,k). A sequence $j_1, j_2, \ldots, j_n$ is, by definition, *a shortest expected processing time–longest expected processing time* (or *SEPT-LEPT*) *sequence* if there is a *k* such that: $\mu_{j_1} < \mu_{j_2} < \ldots < \mu_{j_k}$, and $\mu_{j_k} > \mu_{j_{k+1}} > \ldots > \mu_{j_n}$. In one of the first papers to consider the stochastic flow shop, Pinedo (1982) showed that in a flowshop with *n* jobs and *m* identical machines, with independent, non-overlapping processing time distributions, the expected makespan is minimized if and only if the sequence is a SEPT-LEPT sequence. Pinedo refered to these sequences as "bowl sequences" and proposed the following rule of thumb when trying to minimize the expected makespan:

> Schedule jobs with smaller expected processing times and larger variances in the processing times towards the beginning and end of the sequence, and schedule jobs with larger expected processing times and smaller variances in processing times toward the middle of the sequence.

If the processing times are ordered in the strong stochastic sense, Pinedo showed that the expected makespan is minimized by a particular SEPT-LEPT sequence. Foley and Suresh (1984) showed that in this last case, the SEPT-LEPT sequence that minimizes the expected makespan also minimizes the makespan in the strong stochastic sense.

All of the published results on the stochastic flow shop have restrictions on both the job processing times and the machines. Job processing times are assumed to be non-overlapping or ordered in the strong stochastic sense. These assumptions are not supported by our data. The processing time distributions we observed are what might be called "mildly overlapping". If random variable X is non-overlapping smaller than random variable Y, then $\Pr(X < Y) = 1$; if X and Y are "mildly overlapping", then $\Pr(X < Y)$ is "close to" 1. Published results also assumed machines to be identical, which was again not supported by our data. In the absence of results for arbitrary processing time distributions and non-identical machines, we turned to the development of a heuristic technique that uses the guidelines of the literature (i.e., that SEPT-LEPT sequences were "good" sequences) and incorporates distributional information about our specific problem. As Ignizio (1991) pointed out, in embracing a heuristic approach, we are backing off from a search for an *optimal* schedule to find a *near-optimal* or *acceptable* schedule.

DATA ANALYSIS

Actual data used to model processing times at each station were obtained from two techni-

cal memoranda and a project report provided by the U.S. Army Chemical School (Carr, 1982, Daneker, 1987, and Wolsczak et al., 1981). Data were available for a limited number of vehicle chassis types (tank, armored personnel carrier, and truck) for the DS2 application and rinse stations. Processing station time data were available for the M60 tank (3483 cu. ft.); the M113 armored personnel carrier (1149 cu. ft.); and the M926 5 ton truck (2113 cu. ft.). For these three chassis types (which we call vehicle classes), processing time did not appear to be a linear function of vehicle size (measured in cubic feet), but rather appeared to depend heavily on the body style of the vehicle. Within any particular vehicle class, body style is much the same, and we made the assumption that the distribution of processing time for a given vehicle was a scaled version of that for the representative vehicle in its class. The U.S. Army decontamination manual FM 3-5 (1985) provided estimates of the processing times at the primary wash, interior decontamination, and check stations. The processing times at the primary wash station are estimated to be double those at the rinse station. The processing times at the interior decontamination station are assumed to be a random variable whose expected value depends on the size of the vehicle interior. Trailers which do not have a fixed enclosure require no interior decontamination. The processing times of vehicles at the check station are assumed to be identically distributed for all jobs (vehicle, or vehicle and trailer), since they are a function only of the type of equipment used to verify the thoroughness of decontamination. The only station for which no variability in processing time is assumed is the wait station; processing times at this station were either 10 or 30 minutes depending upon the type of agent used to contaminate the battlefield.

Where actual data were available (i.e., for DS2 application and rinse stations), sample sizes reported were generally rather small, and we found it necessary to rely on expert opinion in our assumptions on processing time distributions. Table 1 shows the distributions used for each vehicle class at each station. In all

Table 1. Detailed equipment decontamination processing time distributions (minutes per vehicle)

Station		Tank Chassis		APC Chassis	Wheeled Vehicles	
Primary Wash		U(21.6, 39.6)		U(9.2, 21.2)	$P(x \leq .8)$ $P(x > .8)$	U(28.2, 34.2) {17.86}
DS2 Appl.		$P(x \leq .8)$ $P(x > .8)$	U(37, 60) {80.25}	U(14.8, 23.8)	$P(x \leq .8)$ $P(x > .8)$	U(26, 48) {73.7}
Wait Time		{10}		{10}	{10}	
Rinse		U(10.8, 19.8)		U(4.6, 10.6)	$P(x \leq .8)$ $P(x > .8)$	U(14.1, 17.1) {8.93}
Interior Decon		U(30, 40)		U(30, 40)	Vehicles only: Vehicles with van/shelter:	U(16, 24) U(30, 40)
Check	CAM	U(16, 24)		U(16, 24)	U(16, 24) except see Note	
	M8A1	U(24, 36)		U(24, 36)	U(24, 36) except see Note	
	M256	U(34, 46)		U(34, 46)	U(34, 46) except see Note	
	Radiac	U(24, 36)		U(24, 36)	U(24, 36) except see Note	

Note: Trailers and trailers with van/shelter have zero processing time at Check station.

cases, our assumptions were discussed extensively with experts at the Chemical School. There is certainly a need for better data on processing times, collected in a controlled manner as input to the scheduling heuristic.

In summary, available data suggest that processing times of jobs (vehicles) are independent random variables whose distributions depend on the station and on the job type (vehicle class and size). Because a changeover cost (idle time) is incurred in the changeover between different types of jobs, all jobs of a given type are to be scheduled together.

MODELING APPROACH

Since the number of possible schedules grows exponentially in the number of jobs, a series of randomly generated small test problems consisting of five and ten jobs were examined in order to develop heuristic rules to reduce the number of schedules considered good "candidate" schedules. The vehicles which made up the various instances of these test problems were randomly selected from a candidate list of the most common military vehicles. The optimal sequences for a total of 40 instances of the five-job problem were determined using a breadth first search. In all but two of the instances an optimal sequence was a shortest expected processing time-longest expected processing time (SEPT-LEPT) sequence. In the two instances that were not SEPT-LEPT, two jobs were transposed. The transposition occurred where a job with a slightly smaller total expected processing time had a significantly larger variance. These observations were confirmed in a series of ten job problems. Again, SEPT-LEPT sequences were always optimal or near-optimal. The "bowl" phenomena was again observed, however, in the larger problem instances, the bowl formed by SEPT-LEPT sequences was not completely smooth, but exhibited sawtooths (see Figure 3), that corresponded to local optima. Our results echoed the results reported by Pinedo (1982), with differences that can be attributed to the fact that Pinedo assumed strictly nonoverlapping processing times. The evidence provided by these empirical results was used to reduce the search space to an examination of SEPT-LEPT sequences. A number of areas were examined to attempt to understand the non-monotonic behavior of the SEPT-LEPT sequences, including the differences in the job variances, their coefficients of variation, and the range between the jobs with the longest and shortest total expected processing time in the sequence. These parameters alone did not seem to shed much light on finding the best overall SEPT-LEPT sequence.

We discovered that if the jobs were placed in ascending order based on their total expected processing time, there appeared to be a corre-

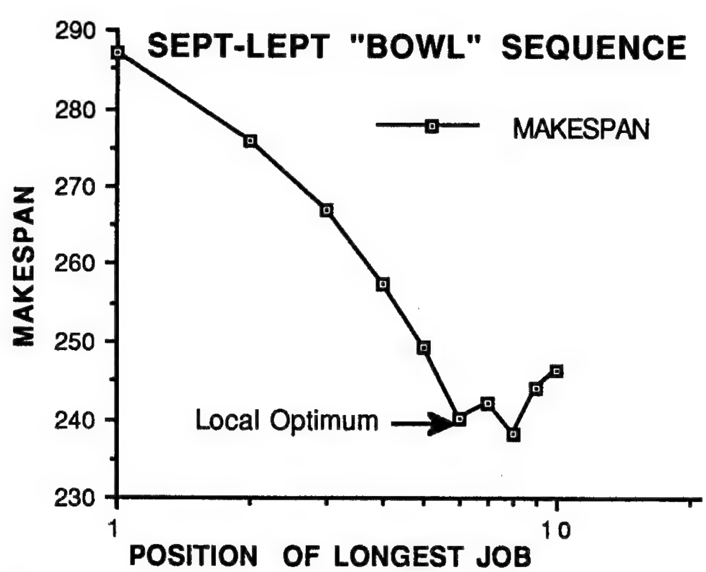

Figure 3. Typical Ten Job Chemical Decontamination Problem

lation between the relative size of the *gap* (differences in the total expected processing time) between adjacent jobs and the location of the start of the LEPT portion of the optimal sequence. It appeared to be better to process the jobs with the shortest total expected processing time first until a job is reached which has a significantly larger total expected processing time than its preceding neighbors. At this point the SEPT portion stops and the LEPT portion of the sequence begins. If a job takes significantly longer than its preceding neighbors, but it does not have the longest total expected processing time, then it seemed to be better to run the longest job and accumulate the idle time due to blocking all at once, since the jobs to follow will have little additional impact on the total idle time.

These observations led to the development of a *Gap Comparison Heuristic* for scheduling the Army's heavy division companies. Figure 4 displays pseudocode for the Gap Comparison Heuristic. Parameters k and m represent discretionary parameters for deciding whether a gap is, respectively, "large enough" to begin the LEPT sequence, or "small enough" to interchange with the neighboring job. In this study, these parameters were set at 1.8 and 0.2, respectively.

The heuristic begins by finding a SEPT-LEPT sequence (i.e., the position of the longest job), and then searches locally for better sequences. The algorithm requires that all jobs be sorted by total expected processing time; they are then placed in a list of nondecreasing total expected processing time. The gaps (difference between the total expected processing time) of adjacent jobs are calculated. Initially, the job with the shortest expected processing time is placed first in the schedule. The remaining jobs in the ordered list are removed in order of increasing expected processing time. If the candidate job has the largest gap, or has a gap which is greater than or equal to some multiple of the average gap size, the LEPT sequence is begun. Otherwise, the job is added to the schedule. Once a job is added to the list, its position is interchanged with that of the neighboring job if the gap between the jobs is small, and the earlier job has a significantly larger processing time variance.

NUMERICAL RESULTS

After considerable testing of the gap comparison heuristic, we used it to generate schedules for the chemical decontamination of each of the Army's 56 heavy division companies. Table 2 displays the estimated makespan of the schedules given by the heuristic for each company. We have given the abbreviation for the company name in column 1 of the table. Table 2 also lists the total number of vehicles and the number of different types of vehicles under the command of each company. We give the makespans of the best and worst SEPT-LEPT

STEP 0. Input expected job processing times $P_1, \ldots, P_n$, and variance of job processing times $V_1, \ldots, V_n$. Select parameters k, m.

STEP 1. Order jobs by increasing expected processing time and label jobs $J_1, \ldots, J_n$.

STEP 2. Compute n-1 gaps $(G_1, \ldots, G_{n-1})$,
$G_i = P_{J_{i+1}} - P_{J_i}$, $i=1,2,\ldots,n-1$.
Compute average gap size
$G = (G_1 + \ldots + G_{n-1})/(n-1)$.

STEP 3. Place J_1 at beginning of schedule.

STEP 4. Repeat for $i=1,2,\ldots,n-1$:
If G_i = largest gap or if $G_i > k\ G$, begin LEPT sequence (add jobs $J_{i+1}, \ldots, J_n$ to schedule in reverse order), and End;
Else, add J_i to schedule and increment i.
If $G_i < m\ G$ and $V_{J_i} < V_{J_{i-1}}$, interchange J_i and J_{i-1}.

Figure 4. Gap Comparison Heuristic

Table 2. Performance of the scheduling heuristic on the chemical decontamination process for 56 heavy division companies

Company	# Vehicle Types	# Vehicles	Best Makespan[1] (hrs)	Worst Makespan[2] (hrs)	Heuristic Makespan (hrs)	Heuristic Accuracy[3]
Air Cav Troop	2	2	1.90	2.06	1.90	0
LRS Det	2	4	2.50	2.67	2.50	0
Atk Hel Co	3	3	2.06	2.31	2.06	0
Tank Co (M1)	3	17	8.10	8.52	8.24	1
HHB Fa Bn (AR)	3	24	7.26	7.47	7.26	0
Tank Co (M60)	4	17	8.37	8.78	8.50	2
Rifle Co BFVS	4	17	6.18	6.69	6.37	1
Rifle Co M113	4	19	6.36	7.19	6.36	0
Antiarmor Co	4	19	6.36	7.19	6.36	0
HHD, FSB	7	13	4.54	5.26	4.63	1
HHD, MSB	7	13	5.00	5.36	5.00	0
Hq & Hq Op Co	7	21	6.44	7.76	6.48	1
TMT Co, MSB	7	99	83.18	83.97	83.32	1
Cav Troop	8	28	8.98	9.99	9.82	4
HHC Sig Bn	8	32	10.78	12.03	10.78	0
EW Co, MI Bn	8	44	12.97	13.65	12.97	0
MP Co	8	49	13.15	14.23	13.15	0
Chemical Co	8	55	23.39	25.12	23.39	0
TGT Acq Btry	10	42	13.52	16.14	13.72	2
HHC/MMC	10	46	13.97	16.02	14.16	3
Fwd Commo Co	10	54	15.56	17.28	15.56	0
Bridge Co	11	24	11.62	11.85	11.68	3
HHT, CBBA	12	27	9.03	10.52	9.07	5
Svc Spt Co, MI	12	36	12.12	13.41	12.69	7
FA Btry 155 mm	12	37	15.83	20.44	15.87	1
HHB, FA Bn (M)	12	39	11.10	12.57	11.10	0
HHB, FA Bn (AR)	12	40	11.35	12.82	11.35	0
Gen Spt Avn Co	12	42	19.31	20.15	19.44	4
Cbt Spt Avn Co	12	43	18.88	19.80	18.91	2
Cmd Op Co, Sig	12	64	18.40	20.31	18.40	0
HHC AR Bde	13	28	8.26	9.68	8.26	0
FA Btry MLRS	13	46	25.87	28.11	25.87	0
Sig Spt Co	13	61	17.40	19.53	17.40	0
Medical Co FSB	14	29	10.19	11.91	10.35	6
HHC, Inf Div	14	63	17.35	20.40	17.35	0
HHC, AR Div	14	64	17.64	20.69	17.64	0
Supply Co, FSB	15	33	16.61	17.57	16.67	3
TAMC, DISCOM	16	43	23.95	24.84	23.95	0
Medical Co MSB	16	43	14.97	17.09	15.13	7
Svc Btry, FA Bn	16	78	42.11	42.81	42.48	6
ADA Btry	17	69	19.32	24.49	19.32	0
HHS Atk Hel Bn	17	51	25.73	27.22	25.79	6

Table 2 Continued

Company	# Vehicle Types	# Vehicles	Best Makespan[1] (hrs)	Worst Makespan[2] (hrs)	Heuristic Makespan (hrs)	Heuristic Accuracy[3]
HHC Engr Bn	18	39	16.90	18.94	17.18	3
HHB Div Arty	18	52	15.64	18.55	15.80	3
HHC Inf Bn BFV	18	130	46.22	52.46	50.21	8
Engr Co	19	50	18.28	20.82	18.31	2
Hvy Maint Co	19	53	21.43	22.95	21.81	4
HHC Tank Bn M1	19	101	42.46	47.84	42.54	1
HHC Inf Bn APC	19	109	36.38	42.62	40.72	9
HHC M60 Tank B	20	96	39.94	44.49	39.94	0
HHB, ADA BN	21	64	17.15	21.67	17.15	0
S&S Co, MSB	21	69	39.60	41.31	39.88	2
Missile Spt Co	22	46	21.85	23.48	22.21	7
LT Maint Co	24	78	41.37	42.57	41.72	7
Maint Co, FSB	25	73	32.24	33.52	32.58	5
HHT, Cav Sqdn	25	95	38.23	42.26	38.32	5
Average	12.5	47	18.84	20.70	19.10	2.21

[1] Expected makespan of the best SEPT-LEPT sequence.
[2] Expected makespan of the worst SEPT-LEPT sequence.
[3] Number of positions off in the position of the longest job

sequences, as determined by an enumerative search.

For these problems, the heuristic produced the best SEPT-LEPT schedule in 24 out of 56 (43%) problems. It produced a schedule which was within 4.7 percent of the best schedule in 95% of the problems. The average time savings over the worst case schedule was 1.86 hours (or 11.1% of the makespan). These results indicate that the heuristic performs very well with this set of problems.

Results for the biological and nuclear decontamination processes were similar to the chemical process results for the 56 different problems. Table 3 contains aggregated results for the 56 companies.

The heuristic produced the best SEPT-LEPT schedule in 14 biological and 15 nuclear decontamination problems, and produced a schedule that was within, respectively, 4.4% and 2.6% of the optimal SEPT-LEPT makespan in 95% of biological and nuclear decontamination problems. Time savings over the worst schedule were again significant in the biological decontamination (an average of 1.09 hours or 7.3% of makespan), and slightly less for the nuclear decontamination (an average of 0.46 hours or 4.8% of makespan).

Table 3. Mean comparative results for decontamination of 56 heavy division companies

Decon	Best Makespan (hrs)	Worst Makespan (hrs)	Heuristic Makespan (hrs)	Average Heuristic Accuracy	Average Improvement (hrs)	Average Improvement (%)
Chemical	18.84	20.70	19.10	2.21	1.86	11.1
Biological	17.90	18.99	18.16	2.59	1.09	7.3
Nuclear	14.80	15.26	14.99	4.57	0.46	4.8

DISCUSSION AND CONCLUSIONS

Scheduling the decontamination of military vehicles is a difficult problem. Job processing times at each station are random variables which are governed by different probability distributions. Furthermore, optimal solutions cannot be calculated and listed in look-up tables in Army manuals because the exact quantity and type of vehicles that will arrive at the decontamination site are not known in advance. Vehicles that are damaged or destroyed on the battlefield may not be processed with their parent company, and the Army usually operates using task organized company/teams (mixtures of tanks and infantry fighting vehicles) whose exact composition varies from battle to battle. In addition, the processing times are mildly overlapping, which further complicates the process of finding the best schedule. Consequently, the heuristic provides a quick means to obtain a good schedule for a problem which in real time is otherwise intractable. Furthermore, the heuristic can be improved by the introduction of local search techniques with very little computational cost. Our results have demonstrated significant improvement over current NBC decontamination practice. Extensive testing of this heuristic on the Army's decontamination problem has produced very good results, and has lead to the scheduling heuristic's consideration for inclusion in future versions of ANBACIS, the U.S. Army Chemical School's automated decontamination decision support system. Finally, since the worldwide proliferation of NBC weapons of mass destruction is still increasing at an alarming rate, the significant reduction in the total processing time of contaminated companies will have an increasing impact on the U.S. Army's ability to defeat its adversaries.

Stochastic scheduling problems are common in practice. The heuristic procedure developed specifically for the decontamination problem has potential application to a wide variety of stochastic scheduling problems, including other decontamination problems (e.g., aircraft). However, we would like to emphasize our view that for heuristic procedures to be valuable, they must be problem-specific; that is, to take advantage of the specific constraints or characteristics of a given problem. Whether the techniques developed in this paper are useful in other contexts depends very heavily on whether the characteristics of this problem (e.g., "mildly overlapping" processing times) are shared by other problems.

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About our Authors

MANOEUVRE WARFARE: SOME CONDITIONS ASSOCIATED WITH SUCCESS AT THE OPERATIONAL LEVEL

by D. Rowland, L. R. Speight and M. C. Keys

David Rowland started his professional career in defence by modeling off road mobility at the UK Military Vehicles Engineering Establishment. Passing on to what is now the Centre for Defence Analysis (High Level Studies), he then had a long association with tactical field trials, producing a string of analyses and reports pertaining to infantry and armoured warfare. Since 1992 he has been the leading light of the Historical Analysis Group at the Centre. He escapes from there to the Welsh mountains whenever he can.

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Martin Keys obtained a Master's degree in experimental space physics before joining the now Centre for Defence Analysis to work on battle modeling and wargaming. He then joined David Rowland in the Historical Analysis Group, and has recently led a study on amphibious warfare. His interest in history stretches to his own genealogy, which he has traced back to 1690.

EXPLORING A RELATIONSHIP BETWEEN TACTICAL INTELLIGENCE AND BATTLE RESULTS

by MAJ E. Todd Sherrill and
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MAJ Todd Sherrill currently serves as the TRAC analyst in the Operations Research Center, West Point. He is an infantry officer with a masters degree in operations research from North Carolina State University. His military experience includes command of an infantry company of the 24th Infantry Division during the Gulf War. Todd's research interest are big game and turkey hunting (making it a nonstochastic venture). He contends that information warfare is nothing new; it's been around ever since man blew his first turkey call.

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ILLNESS INCIDENCE DURING MILITARY OPERATIONS AS A SOFT OPERATIONS RESEARCH FACTOR

by Christopher G. Blood

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REALTIME LEANING OF DOCTRINE AND TACTICS USING NEURAL NETWORKS AND COMBAT SIMULATIONS

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LOCATIONAL ANALYSES OF MILITARY INTELLIGENCE GROUND FACILITIES

by A. Mehrez, M. Eben-Chaime and J. Brimberg

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SCHEDULING OF MILITARY VEHICLES THROUGH THE DELIBERATE NUCLEAR, BIOLOGICAL, AND CHEMICAL DECONTAMINATION PROCESS

by Georgia-Ann Klutke and Valentin Novikov

Georgia-Ann Klutke teaches and conducts research applied probability and operational methods at Texas A&M University. Her research and teaching activities are directed toward a better understanding of the role of variability in manufacturing and service operations. She is on leave in 1996–97 as Program Director for Operations Research and Production Systems at the National Science Foundation and is a former state fencing champion in Virginia and Michigan.

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Editorial Policy and Submission of Papers

Military Operations Research: What's Changed and What Hasn't?

Gregory S. Parnell, Editor, *Military Operations Research*

What hasn't changed?

We want to maintain and improve upon the high quality of articles published in *Military Operations Research*. The first Editor, Dr. Peter Purdue, and his Associate Editors have done a great job of carefully reviewing and selecting outstanding articles. The new editorial board and I will continue the high standards they have set.

What has changed?

The editorial policy has changed. We have developed procedures and instructions to authors that will expedite the review and publication process.

Our new editorial policy (see below) request that authors identify the value of their analysis or research effort described in their paper. Authors must submit a statement of contribution and, for application articles, a letter from a decision-maker stating the benefits of the analysis or research.

The articles submitted to the journal cover many military operations research problem domains and methodologies. In order to assign the most appropriate reviewer, we have identified application areas and methodologies. We have also expanded the number of Associate Editors to insure we have expertise in all of these areas. In addition, we have developed procedures to insure timely review of submitted papers. To help expedite the publication process, we have developed instructions for *Military Operations Research* authors (see below).

EDITORIAL POLICY

The title of our journal is *Military Operations Research*. We are interested in publishing articles that describe *operations research* (OR) methodologies used in important *military* applications. We specifically invite papers that are significant military applications of OR methodologies. Of particular interest are papers that present case studies showing innovative OR applications, apply OR to major policy issues, introduce interesting new problem areas, highlight educational issues, and document the history of military OR. Papers should be readable with a level of mathematics appropriate for a master's program in OR.

All submissions must include a statement of the major contribution. For applications articles, authors are requested to submit a **letter** to the editor—exerpts to be published with the paper—from a **senior decision-maker** (government or industry) stating the benefits received from the analysis described in the paper.

To facilitate the review process, authors are requested to categorize their articles by application area and OR method, as described in Table 1. Additional categories may be added. (We use the MORS working groups as our applications areas and our list of methodologies are those typically taught in most graduate programs.)

INSTRUCTIONS TO *MILITARY OPERATIONS RESEARCH* AUTHORS

The purpose of the "instructions to *Military Operations Research* authors" is to expedite the review and publication process. If you have any questions, please contact Mr. Michael Cronin, MORS Publications Assistant (email: morsoffice@aol.com).

EDITORIAL POLICY AND SUBMISSION OF PAPERS

Composite Group	APPLICATION AREA
I. STRATEGIC	Strategic Operations
	Arms Control
	Revolution in Military Affairs
II. NAVAL WARFARE	Expeditionary Warfare/Power Projection Ashore
	Littoral Warfare/Regional Sea Control
III. AIRLAND CONTINGENCY OPERATIONS	Missle Defense
	NBC Defense
	Mobility
	Air Warfare
	Land Warfare
	Spec Ops/Ops other than War
	Air Defense
	EW & Countermeasures
	Joint Campaign Analysis
IV. SPACE/C3I	C3
	Mil Environmental Factors
	Oper Cont of Space Systems
	OR and Intelligence
V. RESEARCH & DEVELOPMENT	Measures of Effectiveness
	Test & Evaluation
	Unmanned Systems
	COEAs
	Weapon System Acquisition
VI. RESOURCES & READINESS	Soft Factors
	Social Science Methods
	Logistics
	Manpower & Personnel
	Resource Analysis & Forecast Readiness

OR METHODOLOGY
Deterministic Operations Research
Dynamic Programming
Inventory
Linear Programming
Multiobjective Optimization
Network Methods
Nonlinear Programming
Probabilistic Operations Research
Decision Analysis
Markov Processes
Reliability
Simulation
Stochastic Processes
Queuing Theory
Applied Statistics
Categorical Data Analysis
Forecasting/Time Series
Multivariate Analysis
Neural Networks
Nonparametric Statistics
Pattern Recognition
Response Surface Methodology
Others
Advanced Computing
Advanced Distributed Systems (DIS)
Cost Analysis
Wargaming

General

Authors should submit their manuscripts (3 copies) to:

Dr. Gregory S. Parnell, Editor, *Military Operations Research*
Military Operations Research Society
101 South Whiting Street, Suite 202
Alexandria, VA 22304

The manuscript should have camera ready illustrations and an electronic version of the manuscript prepared in WordPerfect or Microsoft Word. Per the editorial policy, please provide:

- authors statement of contribution (briefly describe the major contribution of the article)
- letter from senior decision-maker (application articles only)
- military OR application area(s)
- OR methodology (ies)

Length of Papers

Submissions will normally range from 5-25 pages (double spaced, 12 pitch, including illustrations). Exceptions will be made for applications articles submitted with a senior decision-maker letter signed by the Secretary of Defense.

Figures, Graphs and Charts

Please include camera-ready copies of all figures, graphs and charts. The figure should be of sufficient size for the reproduced letters and numbers to be legible. Each illustration must have a caption and a number which orders the placement of the illustration.

Mathematical and Symbolic Expressions

Authors should put mathematical and symbolic expressions in WordPerfect or Microsoft Word equations. Lengthy expressions should be avoided.

Approval of Release

All submissions must be unclassified and be accompanied by release statements where appropriate. By submitting a paper for review, an author certifies that the manuscript has been cleared for publication, is not copyrighted, has not been accepted for publication in any other publication, and is not under review elsewhere. All authors will be required to sign a copyright agreement with MORS.

Abbreviations and Acronyms

Abbreviations and acronyms (A&A) must be identified at their first appearance in the text. The abbreviation or acronym should follow in parentheses the first appearance of the full name. To help the general reader, authors should minimize their use of acronyms. A list of acronyms should be provided with the manuscript.

Footnotes

We do not use footnotes. Parenthetical material may be incorporated into a notes section at the end of the text, before the acknowledgment and references sections. Notes are designated by a superscript letter at the end of the sentence.

References

References should appear at the end of the paper and be unnumbered and listed in alphabetical order by the name of the first author.

POTENTIAL PAPERS OR SUGGESTIONS FOR THE JOURNAL

Military Operations Research is your journal. I need your help to identify the best articles for submission to the journal! If you have questions about a potential paper or suggestions for articles, please send me e-mail at gsparnell@aol.com.

I'm looking forward to seeing your article in *Military Operations Research*!

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RIST PRIZE CALL FOR PAPERS

MORS offers two prizes for best papers—the Barchi Prize and the Rist Prize. The Rist Prize will be awarded to the best paper in military operations research submitted in response to this Call for Papers. The Barchi Prize will be awarded to the best paper from the entire 65th MORS Symposium, including Working Groups, Composite Groups, and General Sessions.

David Rist Prize: Papers submitted in response to this call will be eligible for consideration for the **Rist Prize**. The committee will select the prize-winning paper from those submitted and award the prize at the 66th MORSS. If selected, the author(s) will be invited to present the paper at the 66th MORSS and to prepare it for publication in the MORS journal, *Military Operations Research*. The cash prize is $1000. To be considered, the paper must be mailed to the MORS office and postmarked no later than **September 30th, 1997.** Please send the original, four copies and the disk.

Richard H. Barchi Prize: Author(s) of those papers selected as the best from their respective Working Group or Composite Group, and those of the General Sessions at the 65th MORSS will be invited to submit the paper for consideration for the **Barchi Prize**. The committee will select the prize-winning paper from among those presented, nominated and submitted. The prize will be presented at the 66th MORSS. The cash prize is $1000. To be considered, the paper must be mailed to the MORS office and postmarked no later than **November 28th, 1997**. Please send the original, four copies and a disk.

Prize Criteria

The criteria for selection for both prizes are valuable guidelines for presentation and/or submission of any MORS paper. To be eligible for either award, a paper must, at a minimum:

- Be original and a self-contained contribution to systems analysis or operations research;
- Demonstrate an application of analysis or methodology, either actual or prospective;
- Prove recognizable new insight into the problem or its solution; and
- Not previously been awarded either the Rist Prize or the Barchi Prize (the same paper may compete for but cannot win both prizes.)

Eligible papers are judged according to the following criteria:

Professional Quality

- Problem definition
- Citation of related work
- Description of approach
- Statement of assumptions
- Explanation of methodology
- Analysis of data and sources
- Sensitivity of analyses (where appropriate)
- Logical development of analysis and conclusions
- Summary of presentation and results

Contribution to Military Operations Research

- Importance of problem
- Contribution to insight or solution of the problem
- Power of generality of the result
- Originality and innovation